How does technological opportunism affect firm performance? The mediating role of resource orchestration

Abstract. Despite widespread acknowledgment of the disruptive effects of digital technologies on firm performance, the mechanisms underlying such effects have not been adequately explained. To fill this gap, we consider two sub-components of technological opportunism (TO), that is, technology-sensing capability (TSC) and technology-responding capability (TRC), and investigate their effects on firm performance from the perspective of resource orchestration (RO). Using survey data from 350 Chinese companies across diverse industries, we find that three RO capabilities – structuring, bundling and leveraging – play different roles in the TO-performance relationship. In particular, resource structuring and leveraging fully mediate the TSC-performance relationship. In contrast, the TSC-performance relationship is fully mediated by resource structuring. Our findings contribute to the growing body of research on technology adoption by offering new theoretical explanations for the mechanisms behind the TO-performance relationship. Our study also helps companies develop effective ways to deal with digital disruption.

Keywords: digital disruption; technological opportunism; resource orchestration; firm performance

1. Introduction

Recent years have seen a surge in interest in digital disruption, which describes how digital technologies change consumer habits, shake up traditional business models and blur industry boundaries (Li, 2022a). To capture how companies keep tabs on the possibilities and dangers presented by new technologies and adapt to them in a timely manner (Mishra and Agarwal, 2010), scholars have proposed *technological opportunism* (TO), which refers to the capabilities of a company to sense technological opportunities and respond to technological developments (Srinivasan et al., 2002). Because TO can promote radical technology adoption (Lucia-Palacios et al., 2014), existing studies generally agree that TO should incur better firm performance (Chen and Lien, 2013). Some leading technology companies with high levels of TO, such as Amazon, Apple and Google, have indeed reaped huge economic gains in the face of digital disruption.

While companies across a variety of industries with high levels of TO recognise the immense potential of digital technologies (Nasiri et al., 2020), the majority have not yet developed an effective way to deal with digital disruption (Li et al., 2022b). A global survey across 131 countries showed that 87% of business executives expected digital technology to bring about an upheaval in their sector, but just 44% were ready for it (Hunt, 2016). Another global report involving 700 digital decision-makers revealed that more than half of companies feared they had less than a year before they began to lose market share if they did not effectively handle digital disruption (PGS, 2016). Most importantly, although some companies high in TO had invested billions of dollars in digital projects in 2019, approximately 70% of them had not attained their goals (Tabrizi et al., 2019). These observations suggest that, in the face of digital disruption, the

TO-performance relationship may vary, and it is not as intuitive as it may appear.

Past studies have primarily explained the processes behind the TO-performance relationship from the perspectives of the resource-based view (RBV) and dynamic capability (Chen and Lien, 2013; Sarkees, 2011). Although these two theoretical perspectives emphasise the importance of valuable resources (Wernerfelt, 1984) and the need to continuously create new resources and knowledge bundles in developing competitive advantage (Teece et al., 1997), they do not reveal in detail how companies should effectively manage their heterogeneous resources. This may incur the real-world phenomenon under which many companies with a certain level of TO agree with the importance of digital technologies (Chirumalla, 2021), but still remain unclear as to how digital technologies may affect companies and how companies should respond to and develop appropriate resource strategies to transform capabilities to performance (Li et al., 2022c). To fill this gap, our study aims to use resource orchestration (RO) theory to unravel the black box regarding how companies manage their resources.

In particular, RO theory suggests that structuring, bundling and leveraging are three major processes for a company's resource management (Sirmon et al., 2007). *Structuring* refers to the process by which a company acquires, accumulates and divests available resources (Sirmon and Hitt, 2009). Some examples include purchasing resources from markets and developing resources internally. *Bundling* is defined as the process of combining several resources to create new capabilities or improve existing ones (Sirmon et al., 2011). A typical example would be to make some minor enhancements to resources that already exist. *Leveraging* refers to the process of organizing, coordinating, and putting to use available resources to generate profits for a company (Sirmon et al., 2011). One such example is making use of resource configurations to aid in the execution of strategy. In the context of digital disruption, technologically opportunistic companies tend to purchase or develop digital technologies; however, digital technologies are new and out of the company's existing resource portfolio. Studies have shown that the mere ownership of resources is not sufficient to ensure the development of competitive advantage (Chirico et al., 2011), and resource-focused activities are more essential than the resources themselves (Sirmon et al., 2011). Hence, to maximise the value of digital technologies, companies must integrate these with the existing resource portfolio, thus involving RO. More importantly, such logic indicates that RO should serve as a critical process that enables technologically opportunistic companies to achieve superior performance. Against this backdrop, our major research question is *How can different aspects of RO mediate the TO-performance relationship*?

To answer the above research question, we polled Chinese companies operating in a variety of economic sectors. More importantly, our work contributes to the expanding literature on technology adoption in the following three ways (Blichfeldt and Faullant, 2021). First, past studies mainly investigate the TO-performance relationship from the perspectives of the RBV (Sarkees, 2011) and dynamic capability (Chen and Lien, 2013). In contrast, we novelly examine such association from the perspective of RO (Sirmon et al., 2007), enriching the present knowledge on how companies should manage their resources.

Second, past studies typically treat TO as a holistic construct (Lucia-Palacios et al., 2016; Mishra and Agarwal, 2010), and do not adequately reveal the differences between two sub-components of TO in affecting firm performance. Because technology-sensing capability (TSC) is related to invisible perceptions, whereas technology-responding capability (TRC) is associated with substantive action (Srinivasan et al., 2002), companies may adopt unique RO activities in response to each kind of TO. In this paper, we explore such differences both theoretically and empirically, enriching the current understanding of the TO-performance relationship.

Third, as RO theory is an emerging theoretical framework, the majority of extant studies are conceptual (Liu et al., 2016; Sirmon et al., 2011). By contrast, we are among the pioneering efforts to demonstrate the diverse mediation effects of three RO processes on the TO-performance relationship in the context of a digital disruption using empirical data. Hence, our study expands the application scope of RO theory (Deligianni et al., 2019), especially in helping academics and practitioners effectively address the challenges of digital disruption.

2. Literature review

2.1 Technological opportunism

Typically, *opportunism* is regarded as a negative trait, referring to behaviour under which business partners do not reveal all facts accurately and seek to benefit themselves at the expense of their partners (Yang et al., 2021). In contrast to the common understanding of the negative form of opportunism, some scholars have investigated a benign form of opportunism in the context of technology adoption (Srinivasan et al., 2002). In particular, TO is an organisational capacity that includes two components: *TSC* and *TRC* (Srinivasan et al., 2002). The former is defined as a company's capacity to learn about and comprehend technology changes in its operating environment, whereas the latter refers to a company's capacity to adapt to technological developments in its environment (Mishra and Agarwal, 2010).

Studies have widely discussed the drivers of TO (Bullini Orlandi et al., 2020). For example, using a sample of American and Spanish companies, Lucia-Palacios et al. (2016) investigated the determinants of TO from the perspective of complementary information technologies (ITs) resources; interestingly, they found that IT usage and IT human capital were two major determinants of TO, and IT vendor support shows diverse impacts on TO across regions. Regarding the outcomes of TO, firm performance is the most cited variable in prior research (Chen and Lien, 2013). Most studies have claimed that TO should have a positive effect on firm performance (Sarkees, 2011). However, not all companies with high levels of TO have achieved superior performance (Hunt, 2016). Hence, some studies further explore the mediators and moderators in the TO-performance relationship (Chen and Lien, 2013).

Even though there have been significant advances achieved by previous studies, there remain certain aspects that may benefit from further improvement. First, most prior research has approached TO as a unified concept (Lucia-Palacios et al., 2016; Mishra and Agarwal, 2010), concealing important distinctions between its two sub-components. Given that companies' perceptions of technological developments and reactions to technological developments need to coordinate different types of resources (e.g., companies' perceptions of technological developments are more related to knowledge of executives, whereas reactions to technological developments require companies to conduct substantial business process reengineering), research that includes more detailed sub-dimensions may produce more nuanced insights regarding firm performance. Second, past studies have primarily explained the TO-performance relationship from the perspectives of the RBV (Sarkees, 2011) and dynamic capability (Chen and Lien, 2013). However, these two theoretical perspectives do not specify how companies should manage their resources (Mikalef et al., 2018), rendering many companies confused and overwhelmed when faced with digital disruption (Li et al., 2022d). Hence, an additional investigation drawing on RO theory that discloses how companies manage their resources is necessary. In short, our study extends and differs from prior research by addressing the aforementioned two gaps.

2.2 Resource orchestration

RO theory evolved from the RBV since the latter emphasises the importance of valuable resources in developing competitive advantage (Wernerfelt, 1984) but does not describe how companies should deploy their resources to achieve synergistic effects (Liu et al., 2016). In contrast, RO theory posits that, to realise the full value of resources for creating competitive advantages, managers should properly structure, bundle and leverage such resources (Sirmon et al., 2011). This is because the consequences of resource deployment are dictated by the joint effects emerging from the combination of linked resources with the focal resource, as opposed to the independent effects of the individual resources (Liu et al., 2016). The mere ownership of resources is not sufficient to ensure the development of competitive advantages (Chirico et al., 2011), and resource-focused activities are more essential than the resources themselves (Sirmon et al., 2011).

Existing research has made some attempts to apply RO theory (Wang et al., 2020a). For example, Liu et al. (2016) used RO theory to explain how supply chain integration matches IT competency to enable Chinese firms to improve their operational and financial performance. Xin et al. (2022) applied RO theory to the context of sustainable development and explore the mechanism by which big data analytics capability influences disruptive green innovation. Similarly, Kristoffersen et al. (2021) employed RO capability to explain how business analytics capability may help companies achieve sustainable performance. Finally, Queiroz et al. (2022) used RO theory to design a framework to understand the drivers of supply chain resilience in the face of severe disruption.

While the above studies help expand the understanding of RO theory, there remain aspects that need to be strengthened. First, most studies related to RO theory are conceptual (Liu et al., 2016; Queiroz et al., 2022), implying that they did not design a measurable variable to substantially describe the process by which a company manages its resources. Second, some studies, such as Kristoffersen et al. (2021) and Xin et al. (2022), have mainly regarded RO capability as a holistic construct in their research framework. However, such simplification does not fully reveal the diverse effects of different RO processes on variables of interest. To the best of our knowledge, only Chen and Tian (2022) and Gligor et al. (2022) used empirical data to confirm the effectiveness of RO theory at the process level. Hence, our study contributes to the application of RO theory by refining this gap in broader contexts.

3. Hypothesis development

In Fig. 1, we develop a research framework based on RO theory to investigate the mechanism underlying the above relationship. In particular, we first divide TO into TSC and TRC. We then investigate how different processes of RO (i.e., structuring, bundling and leveraging) may influence the relationships between these two sub-components of TO and firm performance. In the following, we present the details of each hypothesis.

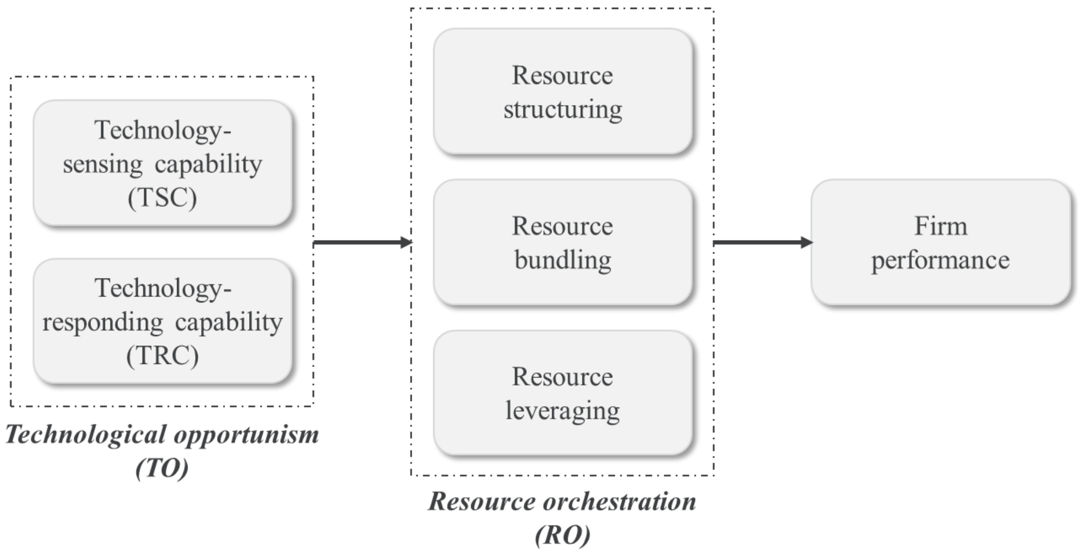

Fig. 1. Research framework

TSC can be comprehended from the perspective of affordance. First, affordance describes the potential for an actor (e.g., a company) to make use of a certain objective item (e.g., a digital technology) or environmental element to accomplish goals (Dremel et al., 2020). Second, an affordance is actualised when an actor discovers the potential for a certain objective item or environmental element (Lehrer et al., 2018); in other words, an actor's actualisation of an affordance is not required for its existence (Faik et al., 2020). Similar to affordance, TSC reflects a company's perceptions regarding how technological advancements change the natural environment, customer needs and untapped market niches (Sarkees, 2011). As long as companies develop perceptions of the potential for technological advancements, whether or not these perceptions are correct, TSC should exist (Srinivasan et al., 2002).

Past studies have argued that TSC helps a company follow and understand technological advancements, as well as the corresponding opportunities and risks, hence enhancing performance (Mishra and Agarwal, 2010). However, a company's perceptions of technological advancements are intangible, whereas the growth in firm performance, such as in revenue, profit and market share, is tangible (Sarkees, 2011). Hence, if a company wants to convert intangible perceptions into tangible income, it must undergo certain processes. Given that a company is essentially a collection of various resources (Wernerfelt, 1984), we primarily analyse these processes from the perspective of RO.

First, studies have shown that companies with considerable TSC regularly search for technology-related information (Srinivasan et al., 2002), which enables them to track the most recent technological advancements and to learn where new technologies can be acquired and accumulated (i.e., resource structuring). A report showed that less than 30% of technology vendors were actively involved in digital transformation projects for the majority of companies in North America and Western Europe (Newman, 2018). Hence, technology-sensitive companies with better access to technology vendor support should theoretically show a greater advantage in the face of digital disruption. Second, companies high in TSC are more likely to recognise incremental opportunities to improve their business operations (Srinivasan et al., 2002), which largely encourages them to conduct resource bundling to achieve cost reductions and efficiency improvements. For example, Tesla built a super factory in Shanghai, which combined digital technologies into manufacturing processes, reducing energy usage per car by 17% compared with the Fremont factory (Cao et al., 2022). Third, companies that are sensitive to technological advances are more likely to grasp the application scenarios of new technologies (Lucia-Palacios et al., 2014), which makes them inclined to allocate diverse resources (i.e., resource leveraging) to find new niche markets. An example is Suning.com, a Chinese e-commerce platform, which explored a new niche market by employing big data to monitor changes in users' online browsing times; importantly, this new niche market allowed Suning.com to maintain economic growth even in the face of COVID-19 (Wang et al., 2020b). In short, technology-sensing companies may better structure, bundle and leverage their resources, which, in turn, improves firm performance.

H1a: Resource structuring mediates the TSC-performance relationship.

H1b: Resource bundling mediates the TSC-performance relationship.

H1c: Resource leveraging mediates the TSC-performance relationship.

In contrast to TSC, TRC is substantial, and can be understood from the perspective of business process reengineering (Srinivasan et al., 2002). Specifically, business process reengineering reflects how a company's processes are analyzed at the most elemental level and then redesigned from the ground up to provide substantial gains in efficiency, economy, and customer satisfaction (Hammer and Champy, 1993). Similar to business process reengineering, which emphasises using technologies to integrate and optimise resources, TRC captures a company's proactive response to emerging technology by reengineering business strategies (Srinivasan et al., 2002). Hence, we focus primarily on RO-related processes underlying the connection between TRC and firm performance.

First, studies have shown that companies high in TRC are less resistant to new ideas and can adjust to new processes and procedures more rapidly (Sarkees, 2011). Because new processes and procedures require companies not only to acquire and accumulate new resources internally or externally but also to strip out obsolete resources, these kinds of companies should have great capability in resource structuring (Sirmon et al., 2007). A case in point is that, during the challenges of COVID-19, companies with strong technological responsiveness invariably incorporated digital technologies into their portfolios (Sheng et al., 2021), with investment in digital projects expanding more than in any other area (McKinsey, 2020). Second, because technology-responsive companies are highly adaptable, they tend to rapidly adopt cutting-edge technology across all levels of the business, from R&D to production to sales (Sarkees, 2011), thus obtaining good capability in resource bundling (Sirmon et al., 2007). A representative example is that, with the increasing consensus regarding low-carbon development, more and more companies have used digital technologies to accelerate the adjustment of their energy structure and optimise the efficiency of manufacturing (Liu et al., 2022). Third, driven by the digital economy, online consumption has maintained rapid growth (Shin et al., 2022). Hence, technology-responsive companies may reallocate resources to create new value for customers. Statistics show that companies that use digital technologies to enhance the consumer experience earn 20–30% improvements in consumer satisfaction and 20–50% growth in their profits (Morgan, 2019). Overall, given that companies with strong technological responsiveness tend to derive value from orchestrating their resource portfolio, we propose the following:

H2a: Resource structuring mediates the TRC-performance relationship.

H2b: Resource bundling mediates the TRC-performance relationship.

H2c: Resource leveraging mediates the TRC-performance relationship.

4. Methods

4.1 Data collection

The digital economy is characterised by high growth, high value and strong sustainability, which can help companies around the world adjust their international industrial chain and supply chain, promote the recovery of the world economy from the impact of COVID-19 and improve the efficiency of economic governance (Times, 2021). With a predicted GDP of 39.2 trillion RMB in 2020, China's digital economy accounts for 38.6 percent of the country's total economy and places it second worldwide (Liu and Liu, 2021). Given these considerations, we primarily surveyed Chinese enterprises, since this can not only give direct direction for Chinese companies on how to effectively deal with digital disruption, but also provide indirect references for comparable companies in other regions.

We designed a questionnaire based on the tested scale (Srinivasan et al., 2002; Sirmon et al., 2007; Chen and Tian, 2022; Li et al., 2022d). Because the original items were in English, we first translated them into Chinese. We also invited a professor of operations management to double-check our back-translation to ensure the concepts were translated correctly. Then, we recruited 50 MBA students to participate in a pre-test, allowing us to gauge respondents' patience regarding the questionnaire's length and tweak the wording accordingly. After that, we partnered with a market research agency with ties to more than 30,000 Chinese companies and randomly distributed our questionnaires to its sample pool. We required that, first, those who filled out the questionnaire be top managers. Second, the companies they represented had to have a certain knowledge of digital technologies. To this end, we designed screening questions; for example, asking respondents to indicate the type of technologies that their business mainly used and to describe the application scenarios of their digital technologies. Only respondents who correctly answered all screening questions could participate in the subsequent investigations. Of the 711 companies contacted, we received 350 valid responses within the allotted time, leading to a response rate of 49.23%. A concise summary of the characteristics of our sample is presented in Table 1.

Table 1. Profile of the sample

Firm information	**Frequency**	**Percentage**
Firm age		
5 years and below	28	8.00
6-10 years	94	26.86
11-15 years	85	24.29
16-20 years	60	17.14
21-25 years	44	12.57
26 years and above	39	11.14
Firm size		
<100	49	14.00
100–299	84	24.00
300-499	60	17.14
500-999	71	20.29
>1000	86	24.57
Ownership		
State-owned	30	8.57
Privately owned	265	75.71
Others (e.g., collective-owned and foreign)	55	15.71

Industry type		
Power	16	4.57
Services	15	4.29
ICTs	123	35.14
Machinery	29	8.29
Textile	27	7.71
Steel	18	5.14
Chemical	18	5.14
Electronic	18	5.14
Food	14	4.00
Equipment	42	12.00
Pharmaceutical	14	4.00
Other sectors	16	4.57

Note: ICTs abbreviate information and communication technologies.

4.2 Measures

The independent variables in the present work were TSC and TRC. We used six items proposed by Srinivasan et al. (2002) to measure them. The dependent variable, firm performance, included four items. These four items were adapted from Li et al. (2022d). The mediating variables were three RO capabilities – structuring, bundling and leveraging. The corresponding nine items were adapted from Sirmon et al. (2007) and Chen and Tian (2022). All items were loaded on a seven-point Likert scale, ranging from '1 = strongly disagree (very low)' to '7 = strongly agree (very high)'. The details of each construct can be found in *Appendix A*. Finally, regarding control variables, we used dummy coding to measure industry type and ownership (Ye et al., 2022), establishment years to 2022 to measure firm age (Li, 2022a) and number of employees to measure firm size (Li et al., 2023).

4.3 Bias checks

Similar to Armstrong and Overton (1997), to assess non-response bias, we used a *t*-test to compare the earliest wave of respondents and the last wave of respondents regarding their responses to firm age and firm size and found no significant differences. In addition, the locations of 350 responding companies were compared against those of 361 non-responding companies. A chi-square test revealed that these two groups did not vary significantly, as all of these companies were located in 30 provinces of mainland China. Overall, no serious concerns about non-response bias emerged.

Because our data were self-reported, another potential concern is associated with common method bias. Motivated by the recommendations of Podsakoff et al. (2003), we controlled and mitigated the risk of common method bias from the following aspects. First, those who took part in the survey were told at the outset that their responses would be kept anonymous and confidential and that they should respond as truthfully as possible. Second, we inserted several reverse items in the questionnaire to check whether respondents answered our questions seriously. Third, we conducted statistical tests. Specifically, we loaded all items into a single factor in the confirmatory factor analysis and found poor model fit indices, with χ^2 = 1100.459, df = 152, χ^2/df = 7.24, IFI = 0.618, CFI = 0.615, GFI = 0.713 and RMSEA = 0.134. We also included the respondents' duration of employment at the current company as a marker variable in our study. As shown in Table 2, there was no statistically significant correlation between the marker variable and any of the focal variables. More importantly, the statistical significance of the correlations between the focal variables was not changed after adjusting for the common method bias.

Table 2. Correlation matrix and discriminant validity

	1	2	3	4	5	6
1. TSC	**0.752**					
2. TRC	0.230**	**0.727**				
3. Resource structuring	0.416**	0.223**	**0.742**			
4. Resource bundling	0.220**	0.205**	0.415**	**0.740**		
5. Resource leveraging	0.301**	0.220**	0.438**	0.652**	**0.731**	
6. Firm performance	0.291**	0.156**	0.403**	0.388**	0.568**	**0.727**
7. Marker variable	0.065	0.017	0.025	0.070	0.088	0.002
Mean	5.468	5.341	5.447	5.459	5.572	5.393
Standard deviation	0.994	0.957	1.068	1.041	1.053	0.808

Note: ** $p < 0.01$; the numbers on the diagonal are the square root of AVEs.

5. Results

5.1 Measurement assessment

The confirmatory factor analysis in the AMOS 24.0 was used to conduct construct validation and found good model fit indices, with χ^2 = 172.849, df = 137, χ^2/df = 1.262, IFI = 0.986, CFI = 0.985, GFI = 0.951 and RMSEA = 0.027. *Appendix A* presents the factor loading of each item, as well as the composite reliability (CR), average variance extracted (AVE) and Cronbach's α for each focal variable. In particular, all factor loadings ranged from 0.662 to 0.848, over the suggested cutoff of 0.5 (Fornell and Larcker, 1981). Moreover, the reliability of the measures was confirmed by the fact that both the CR and Cronbach's α were more than 0.7 for all variables (Bagozzi and Yi, 1988). Furthermore, the AVEs for all variables were larger than 0.5, indicating that the latent variable adequately explained more than half of the variance in the indicators (Fornell and Larcker, 1981). Finally, Table 2 reveals good discriminant validity because the figures on the numbers on the diagonal were larger than the corresponding correlations (Bagozzi and Yi, 1988). Overall, because all conditions were satisfied, use of the proposed variables in our research framework comes with a high level of confidence.

5.2 Hypothesis test

We first estimate the variance inflation factors (VIFs) for two independent variables and three mediators to help address concerns about multicollinearity (Li et al., 2022b). The results show that the VIF values range from 1.098 to 1.894 – much smaller than the threshold of 5 (Hair Jr et al., 2013). Hence, our study has no severe multicollinearity problems.

We then adopt two approaches to test our hypotheses. The first is stepwise hierarchical regression, and the results are summarised in Table 3. Without any mediators, when we involve both TSC and TRC into the regression equation, we find that TSC leads to the increase in firm performance ($\beta = 0.2189$, $p < 0.001$), whereas TRC marginally increases firm performance ($\beta = 0.7973$, $p < 0.1$). One of the primary reasons for this result is the potential link between TSC and TRC, because they are two sub-components of TO (Srinivasan et al., 2002). To eliminate this interference, we enter TSC and TRC into the regression equation separately. The results show that both TSC ($\beta = 0.2249$, $p < 0.001$) and TRC ($\beta = 0.1108$, $p < 0.05$) significantly enhance firm performance.

When the assumed mediators exist, we find that both TSC and TRC have significant effects on three mediators. More importantly, when we include two independent variables and three mediators in the regression equation, only resource structuring ($\beta = 0.1220$, $p < 0.05$) and resource leveraging ($\beta = 0.3763$, $p < 0.001$) are significantly related to firm performance. These results imply that resource structuring and resource leveraging are two factors that link the TO - performance relationship.

Table 3. Regression results

	Resource structuring	Resource bundling	Resource leveraging	Firm performance	
TSC	0.3958***	0.1897**	0.2658***	0.2189***	0.0664
TRC	0.1183*	0.1602**	0.1371*	0.7973†	0.0039
Resource structuring					0.1220*
Resource bundling					-0.0147
Resource leveraging					0.3763***
Firm size	0.0000	0.0000	0.0000	0.0000	0.0000
Firm age	-0.0019	-0.0057	-0.0069	-0.0060	-0.0033
Power	0.8121*	-0.0935	0.1090	0.1646	0.0232
Services	-0.1253	-0.7660*	-0.5024	-0.1582	0.0348
ICTs	0.5179*	0.0986	-0.0830	0.1132	0.0826
Machinery	0.7289*	0.1024	0.3382	0.1136	-0.1011
Textile	0.5615	0.0399	-0.0503	0.0066	-0.0424
Steel	0.4081	0.0707	-0.0752	0.1405	0.1201
Chemical	0.6176	0.0831	-0.0514	-0.0731	-0.1279
Electronic	0.5378	0.1799	0.3788	0.0913	-0.1142
Food	0.4583	0.2147	0.1058	0.1108	0.0182
Equipment	0.8019**	0.0658	0.0841	0.1134	-0.0151
Pharmaceutical	0.4644	0.0519	-0.2895	-0.0282	0.0249
State-owned	0.1215	0.1263	0.2932	-0.0249	-0.1482
Privately owned	-0.0619	0.0433	0.0585	-0.1946	-0.2084*
Constant	5.9235	14.9843	17.1676	16.0590	9.0973
R^2	0.2384	0.1089	0.1555	0.1266	0.3798
F value	6.1136	2.3868	3.5961	2.8320	10.0757

Note: ***, **, *, and † represent significance at 0.001, 0.01, 0.05, and 0.1 levels, respectively.

Although the results based on the stepwise hierarchical regression confirm the existence of a mediating effect, these results do not reveal how different RO capabilities may generate diverse impacts on the relationship between the two sub-components of TO and firm performance. Hence, we consider the second approach; that is, the bootstrap method. We run the PROCESS macro to use the normalised 'Model 4' (Hayes, 2013). In particular, we set TSC (TRC) as the independent variable, three RO capabilities as mediators, firm performance as the dependent variable, and industry type, ownership, firm age, firm size and TRC (TSC) as covariables. With 5,000 bootstrap samples, the estimated results are summarised in Table 4. It can be seen that, while both resource structuring and resource leveraging mediate the TSC-performance relationship, the mediation effect of resource leveraging is larger than that of resource structuring. In contrast, only resource structuring mediates the TRC-performance relationship. These results, thereby, support H1a, H1c and H2a but reject H1b, H2b and H2c.

Table 4. Indirect effects based on the bootstrap approach

Independent variable	Mediators	Effect	BootSE	BootLLCI	BootULCI
TSC	Resource structuring	0.0483	0.0300	0.0003	0.1162
	Resource bundling	-0.0028	0.0157	-0.0288	0.0352
	Resource leveraging	0.1000	0.0446	0.0291	0.2023
TRC	Resource structuring	0.0637	0.0320	0.0059	0.1324
	Resource bundling	0.0144	0.0115	-0.0021	0.0426
	Resource leveraging	-0.0024	0.0127	-0.0260	0.0272

6. Discussion and conclusion

Although most prior studies find a positive TO-performance relationship (Bullini Orlandi et al., 2020; Chen and Lien, 2013), some observations suggest that not all technologically opportunistic companies have achieved superior performance (Li et al., 2022d). To unravel the mystery of this phenomenon, we draw on RO theory to explore the mechanisms through which TO influences firm performance. Using survey data from 350 Chinese companies across diverse industries, we obtain the following interesting findings.

First, although resource structuring and resource leveraging both mediate the TSC-performance relationship, the mediation effect of resource leveraging is larger than that of resource structuring. Some possible reasons are that, unlike resource structuring, which stresses the acquisition, accumulation and destruction of a company's resource portfolio (Sirmon et al., 2007), resource leveraging focuses on how a company should mobilize, coordinate and deploy its resources to profits for shareholders (Sirmon et al., 2011). Hence, in the context of digital disruption, a more straightforward understanding of resource leveraging should be connected to the application scenarios of digital technologies; that is, how companies embed different digital technologies into their business processes to create new value. Recall that TSC reflects a company’s perceptions of technological advancements (Srinivasan et al., 2002), which are intangible. Because application scenarios are the substantive embodiment of invisible perceptions, technologically opportunistic companies have to undergo this process to finally obtain real economic benefits. The findings of Sarkees (2011) indirectly support our arguments; in particular, using data from publicly traded US firms, Sarkees (2011) found that marketing emphasis, referring to the degree to which the marketing department aggressively utilises available resources, positively mediates the TO-performance relationship.

Second, we find that although TRC is positively connected to firm performance, such a link is mediated merely by resource structuring. Some possible reasons are that TRC primarily reflects how a company responds proactively to technological advancements (Mishra and Agarwal, 2010), as exemplified by tracking the technology, establishing alliances to utilise the technology, conducting limited testing for the technology and implementing the technology within the organisation (Srinivasan et al., 2002). Compared with other two aspects of RO, resource structuring is the most basic activity for a company's resource management (Sirmon et al., 2007). Because most companies are inexperienced with new technologies, and have not included them in extent resource portfolios, the first step to positively respond to new technologies is to incorporate new technologies into current resource portfolios, thereby involving resource structuring. The work of Lucia-Palacios et al. (2014) supports our arguments to some extent. Specifically, analysing survey data from 209 American and Spanish companies, Lucia-Palacios et al. (2014) found that TO showed significant relationships with IT adoption and intra-firm diffusion; more importantly, the latter could further enhance performance.

Finally, we do not find that resource bundling plays a substantial mediating role in the connection between the two sub-components of TO and firm performance. According to RO theory, resource bundling is the main process that links resource structuring with resource leveraging (Sirmon et al., 2007). Although we confirm the positive mediation effects of resource structuring and resource leveraging, the non-significant mediation effect of resource bundling implies that this could be the main reason for the following phenomenon: despite widespread acknowledgment of the disruptive effects of digital technologies on business, not all companies with high levels of TO have achieved superior performance. More specifically, if a company knows where to obtain digital technologies and corresponding application scenarios but is unable to integrate digital technologies into its existing resources to construct or alter capabilities, then its performance may not change.

6.1 Theoretical implications

Our study has theoretical implications for the literature on technology adoption (Ukobitz and Faullant, 2022). First, prior research has primarily explained the relationship between TO and firm performance from the perspectives of the RBV (Sarkees, 2011) and dynamic capability (Chen and Lien, 2013). Although both theoretical perspectives are important, and have been widely applied in the context of digital disruption, they have not revealed the detailed processes underlying a company's resource management (Sirmon et al., 2011). Considering that not all technologically opportunistic companies have achieved superior performance (Li et al., 2022d), it is necessary to re-examine the TO-performance relationship from a new theoretical perspective. In short, we are one of the foremost efforts to examine such a relationship from the perspective of RO (Sirmon et al., 2007). Therefore, our study provides a fresh lens for academics via which to reconsider the TO-performance relationship.

Second, in previous research, TO is often approached as a whole construct, particularly when conducting data analysis (Bullini Orlandi et al., 2020). Although the positive correlation between TO and firm performance has been shown by previous research (Lucia-Palacios et al., 2014), findings do not reveal the differences in the two sub-components of TO (Chen and Lien, 2013). Because companies' perceptions of technological developments and reactions to technological developments need to coordinate different types of resources (Srinivasan et al., 2002), investigation from more specific sub-dimensions may yield deeper insights. In contrast to previous studies (Bullini Orlandi et al., 2020), we enrich the current understanding of how TO works by identifying differences in the paths of the two sub-components of TO in influencing firm performance.

Third, as an emerging theoretical framework, the majority of extant studies related to RO theory are conceptual (Sirmon et al., 2011) or based on the case study approach (Gligor et al., 2022). Although several pioneering attempts have used large-scale survey data to expand the application of RO theory in the case of supply chain integration (Liu et al., 2016), sustainable development (Xin et al., 2022), supply chain resilience (Queiroz et al., 2022) and innovation (Deligianni et al., 2019), they typically treat RO capability as a research framework or a holistic construct and do not distinguish the differences in the various types of RO capabilities (Kristoffersen et al., 2021). In short, we are among the first to thoroughly differentiate different types of RO capabilities, after Chen and Tian (2022). More importantly, we demonstrate the unique mediation effects of different RO capabilities on the TO-performance relationship, expanding the current understanding of RO theory.

6.2 Managerial implications

Our findings also provide practitioners with managerial insights, especially for those in China. First, because both TSC and TRC contribute to the improvement of a company's performance, companies should take certain measures to boost them. Studies have suggested that developing a TSC requires companies to accumulate knowledge to learn about new technological possibilities (Mishra and Agarwal, 2010). Therefore, companies should strengthen their organisational learning (Nielsen et al., 2018). Specifically, companies should filter through and integrate knowledge from diverse sources. In addition, companies should develop new ideas, update concepts and innovate knowledge, as well as apply the outcomes of learning to their operations because only in these ways can they enhance the comprehension of the changes in new technologies. Regarding the improvement of TRC, studies have shown that if companies want to improve adaptability, they must create a relatively flexible organisational structure (Giannikas and McFarlane, 2021). To this end, managers should abandon strong organisational control systems. In response, they should actively coordinate diverse activities, and enhance synergy across multiple departments, enabling the entire company to move rapidly and be responsive to technological changes (Herhausen et al., 2021).

Second, to ensure the effectiveness of TSC and TRC in boosting performance, companies should successfully orchestrate their resources, particularly in the aspects of structuring and leveraging. Because resource structuring captures the ability of a company to handle resource acquisition, storage and disposal (Sirmon et al., 2007), and because less than 30% of technology vendors in North America and Western Europe are actively involved in digital transformation projects (Newman, 2018), companies should cultivate strong relationships with their technology vendors to obtain technical support when required (He et al., 2020). To achieve this objective, companies should build a mutual trust mechanism with technology vendors, conduct strategic cooperation meetings with them, and perform frequent satisfaction surveys. Moreover, resource leveraging reflects how a company mobilises, coordinates and deploys its resources to create business value (Sirmon et al., 2011). To expand the outcome of resource utilisation, top executives need to clearly recognise the different application scenarios and potential business value of digital technologies. For this purpose, companies should have a thorough understanding of the benefits and limitations of various digital technologies, thus incorporating them into the current organisational structure and business processes in a variety of ways (Sestino et al., 2020).

6.3 Limitations and future research

Despite these significant contributions, additional investigation is also required. First, while the Chinese setting provides a rich sample base, studies limited to China risk glossing over important regional and cultural variations. Future research could validate our findings in cross-regional and cross-cultural situations, increasing the robustness of our findings. Second, in this paper, we mainly disclose the mediating factors that influence the relationship between TO and firm performance. However, every company is anchored in its institutional environment (Chu et al., 2018). Hence, some institutional factors and situational factors, such as regulatory pressure, customer pressure and competitive pressure, may influence the effectiveness of TO on firm performance. To further enrich our research framework, future research should consider moderators related to the institutional environment. Third, while we have conducted much effort to reduce concerns about common method bias, our study still fails to overcome the limitations of a single data source and sectional data. Future research could consider collecting longitudinal data from different informants in the same company or aggregating survey data with secondary data to make up for this.

Appendix A. Measurement items

Construct	Measurement items
Technology-sensing capability, TSC, adapted from Srinivasan et al. (2002) (CR = 0.795; AVE = 0.566; Cronbach's α = 0.787)	• We are often one of the first in our industry to detect technological developments that may potentially affect our business. (FL = 0.726) • We actively seek intelligence on technological changes in the environment that are likely to affect our business. (FL = 0.673) • We periodically review the likely effect of changes in technology on our business. (FL = 0.848)
Technology-responding capability, TRC, adapted from Srinivasan et al. (2002) (CR = 0.771; AVE = 0.529; Cronbach's α = 0.766)	• We generally respond very quickly to technological changes in the environment. (FL = 0.700) • (R) This business unit lags behind the industry in responding to new technologies. (FL = 0.747) • (R) For one reason or another, we are slow to respond to new technologies. (FL = 0.735)
Resource structuring, adapted from Sirmon et al. (2007) and Chen and Tian (2022) (CR = 0.786; AVE = 0.551; Cronbach's α = 0.785)	• Our company purchases valuable digital resources from technology service providers. (FL = 0.759) • Our company develops valuable digital resources within the company. (FL = 0.701) • Our company gives up less valuable digital resources. (FL = 0.766)
Resource bundling, adapted from Sirmon et al. (2007) and Chen and Tian (2022) (CR = 0.783; AVE = 0.547; Cronbach's α = 0.782)	• Our company bundles digital resources to make minor incremental improvements to existing capabilities. (FL = 0.766) • Our company bundles digital resources to extend current capabilities. (FL = 0.702) • Our company bundles digital resources to create new capabilities with which to address the firm's competitive context. (FL = 0.749)
Resource leveraging, adapted from Sirmon et al. (2007) and Chen and Tian (2022) (CR = 0.775; AVE = 0.535; Cronbach's α = 0.773)	• Our company leverages digital resources to identify the capabilities needed to support capability configurations necessary to exploit opportunities in the market. (FL = 0.720) • Our company leverages digital resources to integrate identified capabilities into effective yet efficient capability configurations. (FL = 0.714) • Our company leverages digital resources to support a chosen strategy, which includes the resource advantage strategy, market opportunity strategy, or entrepreneurial strategy. (FL = 0.759)
Firm performance, adapted from Li et al. (2022d) (CR = 0.817; AVE = 0.528; Cronbach's α = 0.816)	• Growth in return on pre-tax assets (FL = 0.662) • Growth in return on investment (FL = 0.746) • Growth in return on sales (FL = 0.753) • Growth in profit (FL = 0.742)

Note: R stands for reverse items; FL is the abbreviation of factor loadings; the content in the right box is the measurement items of the corresponding construct.

Appendix B. Abbreviation summary

TO	Technological opportunism
TSC	Technology-sensing capability
TRC	Technology-responding capability
RO	Resource orchestration
RBV	Resource-based view
ICTs	Information and communication technologies
FL	Factor loadings

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