Journal of Management & Organization (2024), page 1 of 17
doi:10.1017/jmo.2023.68

RESEARCH ARTICLE

How top leaders' support affects open government data (OGD)-driven innovation capacity of firms: Based on the TOE framework perspective

Yu Wang[1,2,3], Hui Jiang[4], Delong Han[1,2], Mingle Zhou[1,2,3] and Gang Li[1,2]

[1]Key Laboratory of Computing Power Network and Information Security, Ministry of Education, Shandong Computer Science Center (National Supercomputer Center in Jinan), Qilu University of Technology (Shandong Academy of Sciences), Jinan, China; [2]Shandong Provincial Key Laboratory of Computer Networks, Shandong Fundamental Research Center for Computer Science, Jinan, China; [3]SHANDONG SCICOM Information and Economy Research Institute Co., Ltd., Jinan, China and [4]School of Information Management and Artificial Intelligence, Zhejiang University of Finance and Economics, Hangzhou, China
Corresponding author: Gang Li; Email: lig@qlu.edu.cn

(Received 9 February 2023; revised 4 November 2023; accepted 2 December 2023)

Abstract
The innovation value of open government data (OGD) drives firms to the participation in OGD-driven innovation. However, to fully excavate the innovation value of OGD for firms, it is essential to explore the factors and mechanisms that affect OGD-driven innovation capacity. On the basis of the technology–organization–environment (TOE) framework, a theoretical model affecting OGD-driven innovation capacity is proposed for analysis by partial least squares structural equation modeling with 236 sample data from China. The results indicate that top leaders' support positively impacts on OGD-driven innovation capacity in firms. And we also prove that technical competence, organizational arrangement, and innovation support partially mediate the relationship between top leaders' support and OGD-driven innovation capacity on the basis of the TOE framework. Consequently, the findings provide new research perspectives and practical guidance for promoting OGD-driven innovation capacity in firms.

Keywords: OGD-driven innovation capacity; top leaders' support; TOE framework

Introduction

Government agencies collect and publish open government data (OGD), which anyone or any organization may freely access, use, and share (Kalampokis, Tambouris, & Tarabanis, 2011; Kassen, 2013). A significant aspect of OGD is its potential to enhance the value of a firm's current offerings or facilitate the development of new products and services (Magalhaes & Roseira, 2020; Susha, Grönlund, & Janssen, 2015). The present study defines the term 'OGD-driven innovation capacity' as the capacity of a firm to utilize OGD for the purpose of developing innovative products or services. In this paper, we define this capacity as an OGD-driven innovation capacity, i.e., a firm's capacity to employ OGD for product or service innovation.

There is a shortage of study on the capacity to apply OGD at the firm level in the existing academic literature (Magalhaes & Roseira, 2020; Wang & Lo, 2020; Zhao & Fan, 2018). Firms anticipate to enjoy innovative advantages from using OGD (Janssen, Charalabidis, & Zuiderwijk, 2012; Jetzek, Avital, & Bjorn-Andersen, 2014). Unfortunately, deriving possible innovation advantages from a massive dataset like OGD is a difficult procedure. Lack of understanding to use or comprehend the data, inability to mine and apply the information, lack of necessary tools to process the data, and other obstacles can all stymie OGD-driven innovation capacity (Janssen, Charalabidis, & Zuiderwijk, 2012). The issue is clear: which forces within the firm can overcome those obstacles to enhance OGD-driven innovation capacity?

According to previous studies, top leaders' support plays a critical role in enhancing firms' innovation capacity. Weiner, Shortell, and Alexander (1997) demonstrate that when top leaders are supportive of innovation activities, employee engagement increases. At the same time, top leaders' support can give appropriate resources to guarantee that innovation activities run smoothly (Wang & Lo, 2020). In addition, top leaders' support has a key role in interpreting information and ensuring employees know what to do and how to do it (Daft & Weick, 1984; Garcia-Ortega, Lopez-Navarro, & Galan-Cubillo, 2021; Kaplan, Klebanov, & Sorensen, 2012). Despite the prominent role of top leaders' support in firms' innovation activities, there is a lack of robust research confirming the influence of top leaders' support on OGD-driven innovation capacity, and the underlying mechanisms are not yet clear.

Existing research has examined the internal mechanisms of top leaders for firm innovation, including organizational learning (Liao, Chen, Hu, Chung, & Liu, 2017), knowledge sharing (Yu, Wang, Li, & Lin, 2022), work environment (Amabile, Schatzel, Moneta, & Kramer, 2004), and psychological need satisfaction (Reb, Narayanan, & Chaturvedi, 2014). However, most of these studies emphasize employees' psychological sentiments as mediators while ignoring the mediating effects of organizational structure, technological resources, and other objective existences. There is also a lack of a framework to summarize the intrinsic factors that affect OGD-driven innovation capacity. (Amabile et al., 2004; Liao et al., 2017; Reb, Narayanan, & Chaturvedi, 2014) As a result, this study employs the technology–organization–environment (TOE) framework, a general and adaptable innovation adoption framework, to analyze the path of top leaders' support for OGD-driven innovation capacity from three perspectives: technological, organizational, and environmental (Tornatzky, Fleischer, & Chakrabarti, 1990). This study believes that top leaders' support can improve a firm's OGD-driven innovation capacity by enhancing its technical competence, optimizing organizational arrangements, and creating a supportive environment for OGD-driven innovation.

In summary, this study offers two main contributions. First, this study focuses on the internal perspective of firms and examines the influence of top leaders' support on OGD-driven innovation capacity. Second, this study utilizes the TOE framework as a mediator to thoroughly investigate the mechanisms by which top leaders' support influences OGD-driven innovation capacity.

Theoretical background and hypothesis development

OGD-driven innovation capacity

OGD is described as 'making public sector data freely and publicly available for value extraction' (Kalampokis, Tambouris, & Tarabanis, 2011). Recently, governments have increasingly emphasized the innovation value of OGD and taken a series of measures. For example, the UK has established the Open Data User Group for the promotion of private sector innovation in OGD (Open Data User Group, 2012). And China has held competitions such as the 'Zhejiang Open Data Innovation and Application Competition' for the improvement of the innovative application of OGD by individuals, universities, and firms (Zhejiang Open Data Innovation and Application Competition, 2020). These national measures indicate that the government is actively stimulating the innovative application of OGD among users. Simultaneously, firms should also seize the opportunity to overcome multiple obstacles and enhance their capacity to employ OGD for product or service innovation, called OGD-driven innovation capacity.

Most academic research on OGD at the firm level has focused on OGD adoption. For example, Kaasenbrood, Zuiderwijk, Janssen, de Jong, and Bharosa (2015) developed a framework for identifying factors influencing OGD adoption in private organizations. Wang and Lo (2020) constructed a firm-level model of factors influencing OGD adoption based on a socio-technical perspective. However, these research works only examine the factors driving OGD adoption rather than the

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factors impacting firms' OGD-driven innovation capacity. In addition, Jetzek, Avital, and Bjorn-Andersen (2014) developed a framework of OGD-driven innovation generation mechanisms to explain how firms stimulate the generation of economic and social value through OGD. This study, however, ignores a vital premise: whether firms have the capacity to drive innovation and achieve economic and social value through OGD. We must explore OGD-driven innovation capacity as a result of the fact that firms will face technical, organizational, and other obstacles after the introduction of OGD as a new innovation resource. The value of OGD-driven innovation cannot be achieved unless firms have enough capacity to cope with these obstacles.

Top leaders' support and OGD-driven innovation capacity

Top leaders serve as executive sponsors for a given project (Yang, 2008). The role of top leaders in the project is mainly responsible for providing precise guidance and allocating appropriate resources to meet the project's goals (Hsu, Liu, Tsou, & Chen, 2019; Rodríguez, Pérez, & Gutiérrez, 2008; Rosenbloom, 2000). Therefore, in this study, top leaders' support can be defined as an act of proactive sponsorship by providing specific guidance and committing appropriate resources to OGD-driven innovation projects (Hsu et al., 2019; Rodríguez, Pérez, & Gutiérrez, 2008).

The contribution of top leaders' support to OGD-driven innovation capacity manifests itself in two ways. First, from an economic standpoint, OGD does not have value on its own but rather integrates with other factors of production to generate value (Mei, 2018). Top leaders may use their positions and power to deploy the various elements of innovation activities in an efficient manner (Wang & Lo, 2020). This deployment facilitates the integration of OGD with the firm's current resources, helps to overcome the institutional, human, and technological barriers that OGD-driven innovation activities confront, and improves the firm's capacity to recognize commercial opportunities and capitalize on innovation. Simply put, top leaders' support increases the probability of success for OGD-driven innovation by providing the necessary resources.

Second, top leaders' support is able to strengthen the interaction between employees and OGD through their own influence. A key role of top leaders is to interpret information (Daft & Weick, 1984). When top leaders express support for OGD-driven innovation activities, for example, by communicating their goals and benefits through letters, sensitization sessions, etc., they can shift employees' attention to OGD-driven innovation (Garcia-Ortega, Lopez-Navarro, & Galan-Cubillo, 2021; Kaplan, Klebanov, & Sorensen, 2012). Another key role of top leaders' support is to provide clarity of goals, which can help eliminate uncertainty about the adoption of new things within the firm and promote innovation (Kaplan, Klebanov, & Sorensen, 2012; Weiner, Shortell, & Alexander, 1997). In accordance with Koziol-Nadolna (2020), the supporting behaviors of leaders (e.g., articulating goal expectations and providing rewards) can effectively stimulate employees' innovativeness, resulting in a flexible and open innovation firm. In addition, existing literature suggests that top leaders play an important role in promoting organizational learning (Shao, Feng, & Hu, 2017). After introducing the new knowledge of OGD into the firm, top leaders can enhance employees' learning and interaction with OGD by providing open data literacy boot camps (Iryna, Åke, & Marijn, 2015).

In conclusion, this study makes the case that the top leaders' support is, in fact, a proactive leadership approach that qualifies as transformational leadership. By exercising influence, establishing goals and incentives, and other means, this kind of leader may have a direct impact on how the organization views and responds to OGD-driven innovation (Zhou, Wang, Jiang, Li, & Li, 2023). We propose the following hypothesis:

Hypothesis 1a: Top leaders' support plays a proactive role in OGD-driven innovation capacity.

TOE framework as a mediator

OGD-driven innovation, in terms of output results, is the process by which firms use OGD, a new factor of production, to develop new products or services. Multiple variables will undoubtedly impact

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firms' OGD-driven innovation capacity during this phase of innovation adoption and deployment. As a result, we require a broad framework to clarify these impacts and their consequences.

Many researchers have acknowledged Tornatzky and Fleischer's TOE framework as a broad categorization framework for innovation adoption studies (Liang, Wang, Dong, Zhang, & Qi, 2021; Tornatzky, Fleischer, & Chakrabarti, 1990; Wang & Lo, 2016; Zhang, Zhao, Zhang, Meng, & Tan, 2017). The TOE framework, which is highly adaptable and extensively relevant, categorizes the factors influencing innovation adoption as technical, organizational, and environmental. By examining these three aspects, we may gain a better understanding of the direct and indirect effects of top leaders' support on OGD-driven innovation capacity.

Technical competence

OGD is free, gratis, and accessible data and is often viewed as a public good with a non-competitive nature (Zuiderwijk, Janssen, Poulis, & Kaa, 2015). Therefore, access to OGD does not help firms build a competitive advantage. Importantly, firms need to have the technical competence to mine and utilize OGD, discover hidden relationships from data sets, and transform them into innovation paradigms in order to create competitive advantage with OGD (Zuiderwijk et al., 2015; Zurada & Karwowski, 2011).

Hardware and software infrastructure, as well as qualified technical employees, are examples of technical competencies. Data mining requires sophisticated data processing and analysis equipment, such as high-performance CPUs and hard drives, as well as applications such as plug-ins, visualizations, and software libraries (Iryna, Åke, & Marijn, 2015; Seifert, 2004). Firms must have a dependable and modern hardware and software infrastructure in order to increase their data identification, mining, and application capabilities, therefore making OGD more valuable and useful. Furthermore, human competencies and skills are required to comprehend the data (Janssen, Charalabidis, & Zuiderwijk, 2012; Zuiderwijk et al., 2015). Using digital technology to harvest potentially useful information from OGD for business innovation also necessitates the expertise of technical people trained in big data analytics (Ghasemaghaei & Calic, 2019; Wamba et al., 2017).

As mentioned earlier, top leaders' support is a proactive behavior in OGD-driven innovation activities. As a result, top leaders' support may effectively maximize the firm's technology resources to better serve OGD-driven innovation activities. On the one hand, top leaders' support is seen as a significant component impacting an organization's IT resources (Ragu-Nathan, Apigian, Ragu-Nathan, & Tu, 2004; Sohal, Moss, & Ng, 2001). The support of top leaders indicates the emphasis placed on IT resources and can have a direct impact on the procurement and setup of hardware and software infrastructure. On the other hand, top leaders may assure appropriate human resources for OGD-driven innovation activities by deploying in-house technical professionals, recruiting outside technical talent, and increasing general employees' abilities. Finally, we propose the following hypothesis:

Hypothesis 1b: Top leaders' support positively influences technical competence.

Hypothesis 2: Technical competence positively influences OGD-driven innovation capacity.

Hypothesis 2a: Technical competence plays a mediation role between top leaders' support and OGD-driven innovation capacity.

Organizational arrangement

With market competition intensifying and technological change accelerating, the foundation of firms' success lies not only in the introduction of new technologies but also in the organizational and management innovations required to achieve and maintain competitiveness, such as the optimization and upgrading of organizational structures (Teece, 2007; Vaccaro, Jansen, Van Den Bosch, &

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Volberda, 2012). We suggest that top leaders' support can significantly alter organizational arrangement because top leaders have significant sway over organizational resource allocation. We regard organizational arrangement as the institutional setup and staffing arrangement in OGD-driven innovation activities in this study.

When OGD is brought into a firm's innovation production system, it challenges the firm's traditional innovation organizational structure and, unavoidably, shocks the interests of existing departments. To alleviate this shock, top leaders must create a new organizational institution for OGD-driven innovation that avoids conflicts of interest (Zhao & Fan, 2018, 2021). Furthermore, the new organization has resulted in a completely different employment arrangement. Top leaders can use this chance to develop a professional OGD innovation and R&D team (termed an OGD-based R&D organization) by internal staff redeployment and recruitment of new staff (Zhou et al., 2023). Professional employees and an adequate workforce are certain to improve the OGD-driven innovation capacity (Lee & Kwak, 2012).

Smart top leaders can increase OGD-driven innovation capacity by using transformational leadership strategies in this new team, such as fostering innovative thinking via motivating inspiration and effective people cohesiveness through personal care (Chan & Mak, 2014; Zhou et al., 2023). Simultaneously, the new organization results in a reallocation of firm resources (Yukl, Gordon, & Taber, 2002), for example, greater in-house training and more investment in OGD-driven innovation activities. Ambitious employees will take advantage of training, financing, and other possibilities to strengthen OGD-driven innovation capabilities, leading to improved career growth. Finally, we propose the following hypothesis:

Hypothesis 1c: Top leaders' support positively influences organizational arrangement.

Hypothesis 3: Organizational arrangement positively influences OGD-driven innovation capacity.

Hypothesis 3a: Organizational arrangement plays a mediation role between top leaders' support and OGD-driven innovation capacity.

Innovation support

According to the theory of organizational behavior, an organization's survival and growth are dependent on the creativity of its people, and organizations may successfully boost employee creativity by creating a favorable work environment (Amabile & Conti, 1999). We believe that top leaders may create a good work environment by engaging in innovation-support behaviors such as financial assistance, presentations, and training, which stimulate workers to participate in OGD-related knowledge and skills, hence increasing OGD-driven innovation capacity.

While OGD enters the firm's production system as an emerging innovation resource, it also brings new knowledge and new risks (Magalhaes & Roseira, 2020; Zuiderwijk, Helbig, Gil-García, & Janssen, 2014). Employees must learn how to use OGD efficiently to achieve innovation in a situation with inconsistent open standards and potential privacy and security risks. Existing literature indicates that top leaders are good at supporting organizational learning and pushing employees to learn new knowledge and experiment with new ideas (Shao, Feng, & Hu, 2017). Assume that top leaders communicate their support for and even participate in OGD-driven innovation. In such situation, their followers will become more aware of the need of gaining OGD-related knowledge and skills. In addition, top leaders' leadership styles affect employees' attitudes toward innovation. Top leaders with transformational leadership styles, for example, promote radical innovations (Zhou et al., 2023). When the outcome of innovative activities is uncertain, transformational leaders' encouraging and supportive attitudes toward new ideas can boost employees' confidence in innovative activities and reduce their concerns about potential risks, creating a favorable climate for innovation (Shao, Feng, & Hu, 2017; Shin & Zhou, 2003). Finally, we propose the following hypothesis:

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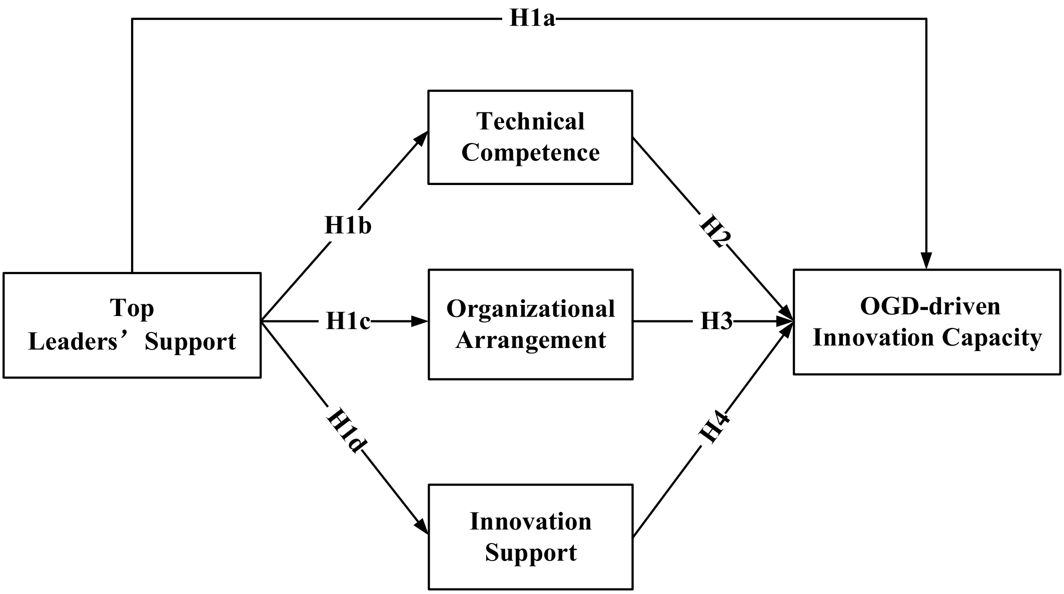

Figure 1. Theoretical model.

Hypothesis 1d: Top leaders' support positively influences innovation support.

Hypothesis 4: Innovation support positively influences OGD-driven innovation capacity.

Hypothesis 4a: Innovation support plays a mediation role between top leaders' support and OGD-driven innovation capacity.

Our theoretical model is shown in Fig. 1.

Data and measures

Data collection

Using the Credamo Questionnaire Platform (https://www.credamo.com/home.html) to collect data, we distributed 300 questionnaires to firms that intend or have performed OGD-driven innovation, with all questionnaires returned. After excluding questionnaires with missing or duplicate options, we obtained 236 valid questionnaires, with an effective response rate of 78.7%. The demographics of the samples are shown in Table 1, and the descriptive statistics of firms are shown in Table 2. The questionnaire is divided into two sections: the first section comprises personal and firm-related information, while the second section comprises questions related to each item and all graded on a 7-point Likert scale.

In practice, respondents' replies may contradict the truth for a variety of reasons, including respondents' failure to grasp the questions, respondents' refusal to answer honestly, and respondents' ambiguity regarding the facts to be replied. As a result, various steps were made in this investigation to assure the quality of the findings. For example, academic experts were widely consulted to revise the questionnaire's items in order to eliminate the possibility that the items would be difficult to understand or unclearly stated; and it was promised that the information in the questionnaire would only be used for academic research and would not be published to the public in order to gain the respondents' trust and to fill in the information honestly. Furthermore, we screened respondents using the

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Table 1. Sample demographics

Items	Number ($N = 236$)	Percentage
Gender		
Male	107	45.34%
Female	129	54.66%
Age (years old)		
≤25	18	7.63%
25–35	162	68.64%
36–45	44	18.64%
≥45	12	5.08%
Education level		
Senior high school or below	8	3.39%
Bachelor's degree	171	72.46%
Master degree or above	57	24.15%
Position level		
Senior level	24	10.17%
Middle level	93	39.41%
Ordinary level	119	50.42%
Role in the OGD-driven innovation		
R&D	89	37.71%
Sales	55	23.31%
Administration	92	38.98%

Table 2. Firm descriptive statistics

Items	Number ($N = 198$)	Percentage
Firm's age (year)		
≤3	0	0
3–5	14	7.07%
5–10	53	26.77%
≥10	131	66.16%
Firm's size (person)		
≤10	0	0
10–50	25	12.63%
51–300	70	35.35%
≥300	103	52.02%
Industry		
Primary industry	8	4.04%
Secondary industry	103	52.02%
Tertiary industry	87	43.94%

Credamo Questionnaire Platform's sample-paying service to guarantee that they were educated about OGD-driven innovation in their firms. The Credamo survey platform has a rigorous and scientific methodology in place to assist this study in inviting qualified target demographics to participate in the survey.

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Measures

Top leaders' support

The measurement of top leaders' support is adapted from Wang and Lo (2020), comprising four items: your top leaders understand the value of OGD for innovation; your top leaders are very enthusiastic about OGD-driven innovation; your top leaders expect to enhance products or develop new products by means of OGD; and your top leaders will provide resources to implement OGD-driven innovation better.

Technical competence

The measurement of a firm's technology competence consists of three items: the firm has OGD-related IT infrastructure (both software and hardware); the firm provides training in OGD-related technology skills and knowledge; and the firm's employees have OGD-related technology and expertise. These items are adapted from Zhao and Fan (2018) and Zhao and Fan (2021).

Organizational arrangement

The measurement of organizational arrangements is adapted from Zhao and Fan (2021) and consists of three items: top leaders' attention and active participation in OGD-driven innovation activities; the establishment of a working group or institution dedicated to OGD-driven innovation activities; and the staffing of professionals responsible for specific activities of OGD-driven innovation activities.

Innovation support

The measurement of innovation support is adapted from Jaw, Lo, and Lin (2010) and consists of four items: adequate budget invested in OGD-driven innovation; adequate time and workforce invested in OGD-driven innovation; encouragement of new ideas from employees on OGD-driven innovation; and adequate rewards for employees who come up with new ideas.

OGD-driven innovation capacity

The measurement of OGD-driven innovation capacity is adapted from Li and Atuahene-Gima (2002) and consists of four items: significant financial resources invested in OGD-driven innovation; improvement of existing products or development of new products through OGD; increased market launch of new products and services through OGD; and increased overall investment in development and marketing for OGD-driven innovation.

Control variables

First, the firm's age was controlled as a result that younger firms may have a higher incentive for innovation than mature firms (Balasubramanian & Lee, 2008). Furthermore, we controlled the firm's size, as size typically leads to economies of scale, allowing larger firms to obtain competitiveness over smaller firms (Dukeov, Bergman, Heilmann, Platonov, & Jaschenko, 2018; Hansen, 1992). Third, we additionally controlled for industry category, assigning a value of '1,' '2', and '3' to primary industry, secondary industry, and tertiary industry, respectively. Ultimately, as Slevin and Covin (1997) point out, hostility can pose a threat to organizational survival and growth and may affect the organization's innovation decisions and performance. We chose hostility as another control variable and measured it by adapting the two-item scale of Slevin and Covin (1997). The reliability of this scale was 0.84.

Data analysis method

The variance-based method (partial least squares structural equation modeling [PLS-SEM]) was employed for data analysis, and SmartPLS software was applied for empirical tests. The PLS-SEM method is appropriate for complicated models with multiple constructs, indicators, and structural paths, as well as for small sample data with non-normal distribution (Hair, Ringle & Sarstedt, 2011). Therefore, based on the model in this paper, the justifications for choosing the PLS-SEM method

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Table 3. Outer loadings and VIF

	TLS	TC	OA	IS	OGDIC	VIF
TLS1	**0.81**					1.37
TLS2	**0.78**					1.61
TLS3	**0.75**					1.47
TLS4	**0.71**					1.47
TC1		**0.83**				1.54
TC2		**0.78**				1.39
TC3		**0.80**				1.41
OA1			**0.81**			1.45
OA2			**0.85**			1.79
OA3			**0.84**			1.75
IS1				**0.78**		1.59
IS2				**0.76**		1.48
IS3				**0.73**		1.40
IS4				**0.81**		1.58
OGDIC1					**0.79**	1.59
OGDIC2					**0.81**	1.65
OGDIC3					**0.73**	1.38
OGDIC4					**0.78**	1.56

Note. TLS = top leaders' support; TC = technical competence; OA = organization arrangement; IS = innovation support; OGDIC = OGD-driven innovation capacity; VIF = variance inflation factor.
Bold values are the outer loadings of the constructs.

are as follows: (1) the model is reasonably sophisticated (numerous constructs, indicators, and paths); (2) the sample size is comparatively limited (236); and (3) the data are non-normal distributed. Furthermore, in this study, the recommended two-step procedure was applied to assess the measurement and structural models, respectively (Hair et al., 2011).

Analysis and results

Measurement model

All constructs and indicators in this measurement model were evaluated for reliability and validity. We first evaluated the reliability of each indicator with suggested loadings above 0.7 (Hair, Risher, Sarstedt, & Ringle, 2019). It is shown in Table 3 that all out loadings are above 0.7, suggesting good indicator reliability. And the internal consistency reliability was evaluated on the basis of three criteria, that is Cronbach's α (CA), ρ_A, and composite reliability (CR) (Hair et al., 2019). It is shown in Table 4 that the values of CA, ρ_A, and CR for all constructs are higher than 0.7 (Benitez, Henseler, Castillo, & Schuberth, 2020), indicating good reliability of the measurement scales.

Convergent validity is evaluated by the average variance extracted (AVE) (Fornell & Larcker, 1981), and the AVE value above 0.5 is considered that the construct explains no less than 50% of the variance of its indicators (Hair et al., 2011). It is shown in Table 4 that all AVE values are above 0.5 and have favorable convergent validity. Discriminant validity, usually evaluated by the Fornell–Larcker criterion, is the degree to which a construct indeed differs from other constructs (Fornell & Larcker, 1981), requiring that the square root of AVE should be above the correlation between constructs (Hair et al., 2011). Table 4 indicates that the measurement model is in favorable discriminant validity.

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Table 4. Reliability and discriminant validity of the constructs

	CA	ρ_A	CR	AVE	TLS	TC	OA	IS	OGDIC
TLS	0.76	0.77	0.85	0.58	**0.76**				
TC	0.73	0.73	0.85	0.65	0.65	**0.80**			
OA	0.78	0.78	0.87	0.69	0.66	0.71	**0.83**		
IS	0.77	0.78	0.85	0.59	0.63	0.58	0.62	**0.77**	
OGDIC	0.78	0.78	0.86	0.60	0.69	0.68	0.75	0.67	**0.78**

Note. TLS = top leaders' support; TC = technical competence; OA = organization arrangement; IS = innovation support; OGDIC = OGD-driven innovation capacity.
Bolded values are the square root of the average variance extracted (AVE).

Table 5. Descriptive statistics and correlation result

	N	M	SD	TLS	TC	OA	IS	OGDIC
TLS	236	5.93	0.65	1				
TC	236	5.88	0.76	0.65	1			
OA	236	5.76	0.95	0.66	0.71	1		
IS	236	6.04	0.66	0.63	0.58	0.62	1	
OGDIC	236	5.80	0.71	0.69	0.68	0.75	0.67	1

Note. M = mean; SD = standard deviation; TLS = top leaders' support; TC = technical competence; OA = organization arrangement; IS = innovation support; OGDIC = OGD-driven innovation capacity.

In addition, Table 5 shows that a total of 236 respondents participated in this survey, giving the mean and standard deviation, and giving the correlation between all constructs. The results in Table 5 show that there is a good correlation between the various constructs, which is suitable for further hypothesis analysis.

Structural model

Following the evaluation of the measurement model, the structural model is examined. PLS-SEM typically tests the relationships among the constructs of the structural model by means of examining the coefficient of determination (R^2), significance and correlation of the path coefficients, and effect sizes (f^2) (Benitez et al., 2020; Hair et al., 2019). In this stage, we evaluate the structural model to determine whether the hypotheses presented earlier are valid.

Since the relationship between the constructs is a series of regression equations, we need to check multicollinearity to ensure that it does not bias the regression results (Hair et al., 2019). In accordance with Benitez et al. (2020), the variance inflation factor was selected to check multicollinearity. It is shown in Table 3 that all variance inflation factor values are under the standard threshold of 3, indicating an absence of multicollinearity.

The evaluation results of the structural model are obtained by running the bootstrapping program with 5,000 iterations of subsamples. Figure 2 indicates the model evaluation results, where the explained variance of endogenous variables (R^2) as well as the standardized path coefficients (β) of endogenous variables are given. As is illustrated in Fig. 2, top leaders' support ($\beta = 0.21$, $p < .05$), technical competence ($\beta = 0.15$, $p < .05$), organizational arrangement ($\beta = 0.37$, $p < .001$), and innovation support ($\beta= 0.22$, $p < .05$) play a significant role in OGD-driven innovation capacity. Consequently, hypotheses H1a, H2, H3, and H4 are supported. In addition, top leaders' support plays a significant role in technical competence ($\beta = 0.65$, $p < .001$), organizational arrangement ($\beta = 0.66$, $p < .001$), and innovation support ($\beta = 0.63$, $p < .001$), respectively. Thus, hypotheses H1b, H1c, and H1d are supported. Table 6 shows the results of all direct hypotheses.

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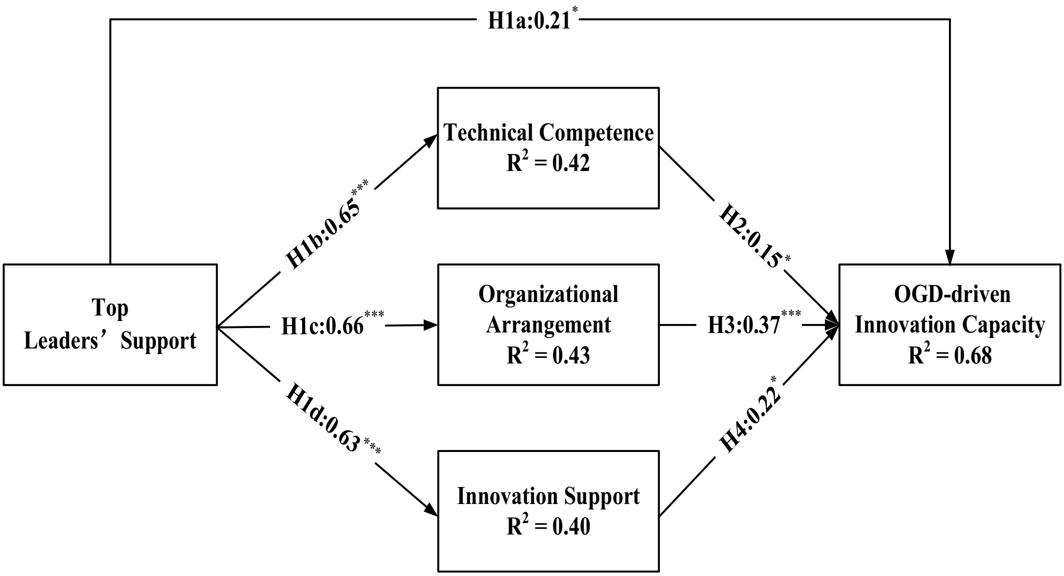

Figure 2. Estimated relationships of the structural model.

Table 6. The results of all direct hypotheses

Hypotheses	Direct path	β	SD	*T* value	*p* value	LLCI	ULCI	Supported
H1a	TLS → OGDIC	0.21*	0.08	2.80	.01	0.06	0.36	Yes
H1b	TLS → TC	0.65***	0.05	13.62	.00	0.55	0.74	Yes
H1c	TLS → OA	0.66***	0.04	14.78	.00	0.57	0.74	Yes
H1d	TLS → IS	0.63***	0.05	13.78	.00	0.54	0.72	Yes
H2	TC → OGDIC	0.15*	0.07	2.03	.04	0.01	0.30	Yes
H3	OA → OGDIC	0.37***	0.09	3.86	.00	0.19	0.55	Yes
H4	IS → OGDIC	0.22*	0.09	2.49	.01	0.04	0.39	Yes

Note. TLS = top leaders' support; OGDIC = OGD-driven innovation capacity; TC = technical competence; OA = organizational arrangement; IC = innovation support; SD = standard deviation; LLCI = low-level confidence interval; ULCI = up-level confidence interval.
*$p < .05$, ***$p < .001$.

R^2, known as in-sample predictive power, is often used to assess the variance explained of all endogenous constructs (Benitez et al., 2020; Hair et al., 2019), which is also a measurement of the explanatory power of a model (Hair et al., 2019). On the measurement scale, the R^2 values of 0.75, 0.50, and 0.25 are regarded as substantial, moderate, and weak levels of explanatory power, respectively (Hair et al., 2011; Henseler, Ringle, & Sinkovics, 2009). It is illustrated in Fig. 2 that our structural model explicates 42% of the variance (R^2) in technical competence, 43% in organizational arrangement, 40% in innovation support, and 68% in OGD-driven innovation capacity, respectively. Consequently, our model has moderate explanatory power.

In addition to evaluating the R^2 as the explanatory power of all endogenous constructs, the model's quality should be assessed by the effect sizes (f^2) (Liang et al., 2021). In case that an exogenous construct is left out from the model, we can use f^2 to assess the effect of this omitted construct on the R^2 value of an endogenous construct (Mikalef, Krogstie, Pappas, & Pavlou, 2020). Based on the guideline, the f^2 values of 0.02, 0.15, and 0.35 refer to small, medium, and large effect sizes, respectively (Hair et al., 2019). f^2 effect sizes' results of all exogenous constructs are shown in Table 7. Top leaders' support (0.06), technical competence (0.03), and innovation support (0.08) have a small effect size

Table 7. The results of f^2 effect sizes

Constructs	R^2	f^2	Explanatory power
Top leaders' support		0.06	Small
Technical competence		0.03	Small
Organizational arrangement		0.17	Medium
Innovation support		0.08	Small
OGD-driven innovation capacity	0.68		

Table 8. Mediation effect test

Mediating path	Effect	β	SD	T value	p value	LLCI	ULCI	Result
H2a: TLS → OGDIC through TC	Direct	0.21*	0.08	2.80	.01	0.06	0.36	Complementary
	Indirect	0.10*	0.05	2.01	.04	0.00	0.20	Partial mediation
H3a: TLS → OGDIC through OA	Direct	0.21*	0.08	2.80	.01	0.06	0.36	Complementary
	Indirect	0.24***	0.07	3.66	.00	0.12	0.38	Partial mediation
H4a: TLS → OGDIC through IS	Direct	0.21*	0.08	2.80	.01	0.06	0.36	Complementary
	Indirect	0.14*	0.06	2.55	.01	0.02	0.24	Partial mediation

Note. TLS = top leaders' support; OGDIC = OGD-driven innovation capacity; TC = technical competence; OA = organizational arrangement; IS = innovation support; LLCI = low-level confidence interval; ULCI = up-level confidence interval.
*$p < .05$, ***$p < .001$.

on OGD-driven innovation capacity. In contrast, organizational arrangement (0.17) has a medium effect size toward OGD-driven innovation capacity.

Mediating effect test

Previous research has frequently used the four-step Sobel test approach to assess for mediating effects (Arpaci, Kesici, & Baloğlu, 2018; Sobel, 1982). Nevertheless, the Sobel test is inappropriate for analyzing indirect effects (Nitzl, Roldan, & Cepeda, 2016; Preacher & Hayes, 2008), and in this study, the Sobel test is unnecessary. As a result that after 5,000 iterations of the bootstrapping procedure, PLS can test the direct and indirect effects of the model (Arpaci, Kesici, & Baloğlu, 2018; Hair, Hult, Ringle, & Sarstedt, 2017; Preacher & Hayes, 2008) and still obtain a high statistical power in the case of small samples (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Henseler, 2010).

The mediating effect test results for this study's model are shown in Table 8. On the basis of the results in Table 8, we conclude that the direct and indirect effects (mediating paths) of top leaders' support on OGD-driven innovation capacity are of significance regardless of whether the technical competence, organizational arrangement, or innovation support is introduced. Consequently, we confirm that technical competence, organizational arrangement, and innovation support all partially mediate the relationship between top leaders' support and OGD-driven innovation capacity, and hypotheses H2a, H3a, and H4a are all supported.

Discussion

Based on the results of PLS-SEM, this study first confirms the positive correlation between top leaders' support and OGD-driven innovation capacity. This finding highlights the importance of top leaders' support for firms' adoption and application of OGD while keeping consistent with earlier studies on the relationship between top leaders' support and firm innovation (Hsu et al., 2019; Yu et al., 2022). Furthermore, technical competence, organizational arrangement, and innovation support play a partial mediating role between top leaders' support and OGD-driven innovation capacity. This implies

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that top leaders' support is not an empty promise but can enhance OGD-driven innovation capacity by influencing the internal state of the organization.

Second, organizational arrangement has the highest degree of influence on OGD-driven innovation capacity ($\beta = 0.37$, $p < .001$) among all factors and the largest mediating effect ($\beta = 0.24$, $p < .001$) between top leaders' support and OGD-driven innovation capacity. As mentioned by Andrews, Beynon, and McDermott (2016), organizational structure is crucial in determining the emergence of high or low capacity. Our study further confirms that flexible, effective, and well-staffed organizational arrangements are a key factor in enhancing OGD-driven innovation capacity.

Third, technical competence has the smallest direct effect on OGD-driven innovation capacity ($\beta = 0.15$, $p < .05$) and the smallest mediating effect ($\beta = 0.10$, $p < .05$) between top leaders' support and OGD-driven innovation capacity. There may have two explanations for this: on the one hand, with the increase of highly educated population, firms can efficiently recruit relevant technical employees, and those well-educated employees can easily acquire OGD-related knowledge and skills through training. On the other hand, new generation computing resources, such as cloud computing services, provide hardware and software resources to firms on demand through the network, reducing the cost of hardware and software configuration for firms (Khayer, Bao, & Nguyen, 2020). Therefore, technical competence is not a major influencer of OGD-driven innovation capacity.

Finally, the direct effect ($\beta = 0.22$, $p < .05$) of innovation support on OGD-driven innovation capacity is as moderate as the mediating effect ($\beta = 0.14$, $p < .05$) between top leaders' support and OGD-driven innovation capacity. Although the innovation support is not the most critical factor influencing OGD-driven innovation capacity, it cannot be ignored. Creating a supportive environment for OGD-driven innovation can subconsciously raise employees' awareness of enhancing OGD-driven innovation capacity.

Conclusion

Top leaders' support plays an important management and decision-making role in firms' OGD-driven innovation activities. Using the TOE framework, this paper develops a theoretical model to understand the impact of top leaders' support on OGD-driven innovation capacity. The findings of this study indicate that top leaders' support significantly affects OGD-driven innovation capacity. The results also show that technical competence, organizational arrangement, and innovation support partially mediate the relationship between top leaders' support and OGD-driven innovation capacity.

Theoretical and practical implications

Theoretical implications

Several theoretical implications are concluded below. First, prior literature has explored a large number of OGD-related topics at the governmental level, such as institutional capacity (Zhao & Fan, 2018), policy comparison (Bates, 2014; Chatfield & Reddick, 2018), adoption (Wang & Lo, 2016), and implementation evaluation (Zuiderwijk & Janssen, 2014). Some scholars have gradually shifted their research from the government level to the firm level, with research topics covering adoption (Kaasenbrood et al., 2015; Wang & Lo, 2020), value generation mechanisms (Ahmadi Zeleti, Ojo, & Curry, 2016; Leviäkangas & Molarius, 2020), and realization paths (Jetzek, Avital, & Bjorn-Andersen, 2014). However, few studies have addressed the capacity of firms to leverage OGD for innovation. This paper shifts the focus of the current study to the firm's OGD-driven innovation capacity.

Second, this study developed a model and verified its validity through empirical testing to advance the understanding of OGD-driven innovation capacity. Based on the TOE framework, a model has been proposed to identify the intrinsic drivers that influence OGD-driven innovation capacity, which has good explanatory power (67.7%). Unlike the theoretical models commonly used in technological innovation (e.g., Unified Theory of Acceptance and Use of Technology, Technology

https://doi.org/10.1017/jmo.2023.68 Published online by Cambridge University Press

Acceptance Model, and Task-Technology Fit), this paper provides a different theoretical perspective for researchers of OGD-driven innovation capacity at the firm level.

Furthermore, the findings of this paper make up for and extend the research on firms' innovation capacity. Previous literature has validated the positive contribution of top leaders' support to a firm's innovation capacity on different topics (Guo, Pang, & Li, 2018; Talke, Salomo, & Rost, 2010; Yu et al., 2022). And the findings of this study further validate that top leaders' support has significant direct and indirect effects on a new innovation capacity such as OGD-driven innovation capacity. In addition, prior literature has examined the impact on innovation by primarily incorporating top leaders' support into organizational arrangements (Zhao & Fan, 2021). This study argues that top leaders' support affects organizational arrangements such as institutional settings and staffing, which in turn has an effect on innovation capacity.

Practical implications

Several practical implications are summarized below. To begin with, top leaders' support is essential for improving OGD-driven innovation capacity. We encourage top leaders to attach great importance to the innovation value of OGD and optimize the configuration of technology and management within the organization from the top down, in order to prepare for the realization of OGD-driven innovation capacity. Second, the technical competence is essential, although it is not the most critical factor for firms to improve their OGD-driven innovation capacities. Firms are required to keep up with the next generation of information technology to avoid losing competitive advantage continuously. For example, top leaders can enhance the firm's technical competence by training and developing relevant technological talents and introducing next-generation information technology (e.g., cloud computing). Third, top leaders should realize that verbal expressions of support for OGD-driven innovation are inadequate; they must be followed by action. For example, they can commit resources to establish OGD-driven innovation-related organizations and rationalize staffing arrangements. The organizational arrangement can reflect the firm's readiness, and a reasonable and adequate organizational arrangement can fully optimize the firm's workforce and management and enhance the ability of OGD-driven innovation. Finally, the innovation environment within the organization should be given attention. Top leaders should motivate employees to improve their OGD-driven innovation capacities by providing a stable innovation environment (e.g., training, financial support, reward, and punishment system).

Limitations and future directions

Although this study thoroughly examined the factors and mechanisms that influence the OGD-driven innovation capacity, there are some limitations listed as follows. First, the sample data in this paper is relatively small (236); therefore, we expect future studies to expand the sample size to examine better the factors influencing OGD-driven innovation capacity. Second, this study was exclusively undertaken in China. Although the findings have some implications for other countries to enhance OGD-driven innovation capacity, more research is required in the future in multi-regional and multicultural contexts for caution, particularly given the relative lack of research in this field. Finally, this study focuses on how factors internal to the firm (e.g., top leaders' support) influence OGD-driven innovation. Future research could incorporate factors external to the firm (e.g., external pressures and government support) to develop new research models that would enrich the research perspective.

Acknowledgements. This work was supported by the Shandong Provincial Natural Science Foundation (NO.ZR2022QG016), the National Social Science Fund of China (NO.22FGLB010), and the Taishan Scholars Program (NO.tscy20221110).

References

Ahmadi Zeleti, F., Ojo, A., & Curry, E. (2016). Exploring the economic value of open government data. *Government Information Quarterly*, *33*(3), 535–551.

Amabile, T. M., & Conti, R. (1999). Changes in the work environment for creativity during downsizing. *Academy of Management Journal*, *42*(6), 630–640.

Amabile, T. M., Schatzel, E. A., Moneta, G. B., & Kramer, S. J. (2004). Leader behaviors and the work environment for creativity: Perceived leader support. *The Leadership Quarterly*, *15*(1), 5–32.

Andrews, R., Beynon, M. J., & McDermott, A. M. (2016). Organizational capability in the public sector: A configurational approach. *Journal of Public Administration Research and Theory*, *26*(2), 239–258.

Arpaci, I., Kesici, Ş., & Baloğlu, M. (2018). Individualism and internet addiction: The mediating role of psychological needs. *Internet Research*, *28*(2), 293–314.

Balasubramanian, N., & Lee, J. (2008). Firm age and innovation. *Industrial and Corporate Change*, *17*(5), 1019–1047.

Bates, J. (2014). The strategic importance of information policy for the contemporary neoliberal state: The case of Open Government Data in the United Kingdom. *Government Information Quarterly*, *31*(3), 388–395.

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management*, *57*(2), 103168.

Chan, S. C., & Mak, W. (2014). Transformational leadership, pride in being a follower of the leader and organizational commitment. *Leadership & Organization Development Journal*, *35*(8), 674–690.

Chatfield, A. T., & Reddick, C. G. (2018). The role of policy entrepreneurs in open government data policy innovation diffusion: An analysis of Australian Federal and State Governments. *Government Information Quarterly*, *35*(1), 123–134.

Daft, R. L., & Weick, K. E. (1984). Toward a model of organizations as interpretation systems. *Academy of Management Review*, *9*(2), 284–295.

Dukeov, I., Bergman, J.-P., Heilmann, P., Platonov, V. V., & Jaschenko, V. V. (2018). A firm's age and size as determinants for its organizational innovativeness. *Journal of Innovation Management*, *6*(3), 98–133.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Garcia-Ortega, B., Lopez-Navarro, M. A., & Galan-Cubillo, J. (2021). Top management support in the implementation of industry 4.0 and business digitization: The case of companies in the main European stock indices. *IEEE Access*, *9*, 139994–140007.

Ghasemaghaei, M., & Calic, G. (2019). Does big data enhance firm innovation competency? The mediating role of data-driven insights. *Journal of Business Research*, *104*, 69–84.

GOV.UK. (2012). *Open Data User Group*. Retrieved August 24, 2022, from https://www.gov.uk/government/groups/open-data-user-group.

Guo, G., Pang, X. Q., & Li, W. (2018). The role of top management team diversity in shaping the performance of business model innovation: A threshold effect. *Technology Analysis & Strategic Management*, *30*(2), 241–253.

Hair, J. F. Jr, Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)*. New York: SAGE.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24.

Hair, J. F. Jr, Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM). *European Business Review*, *26*(2), 106–121.

Hansen, J. A. (1992). Innovation, firm size, and firm age. *Small Business Economics*, *4*(1), 37–44.

Henseler, J. (2010). On the convergence of the partial least squares path modeling algorithm. *Computational Statistics*, *25*(1), 107–120.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In R. R. Sinkovics & P. N. Ghauri (Eds.), *New challenges to international marketing* (pp. 279–319). Bingley: Emerald Group Publishing Limited.

Hsu, H. Y., Liu, F. H., Tsou, H. T., & Chen, L. J. (2019). Openness of technology adoption, top management support and service innovation: A social innovation perspective. *Journal of Business and Industrial Marketing*, *34*(3), 575–590.

Iryna, S., Åke, G., & Marijn, J. (2015). Organizational measures to stimulate user engagement with open data. *Transforming Government: People, Process and Policy*, *9*(2), 181–206.

Janssen, M., Charalabidis, Y., & Zuiderwijk, A. (2012). Benefits, adoption barriers and myths of open data and open government. *Information Systems Management*, *29*(4), 258–268.

Jaw, C., Lo, J.-Y., & Lin, Y.-H. (2010). The determinants of new service development: Service characteristics, market orientation, and actualizing innovation effort. *Technovation*, *30*(4), 265–277.

Jetzek, T., Avital, M., & Bjorn-Andersen, N. (2014). Data-driven innovation through open government data. *Journal of Theoretical and Applied Electronic Commerce Research*, *9*(2), 100–120.

Kaasenbrood, M., Zuiderwijk, A., Janssen, M., de Jong, M., & Bharosa, N. (2015). Exploring the factors influencing the adoption of open government data by private organisations. *International Journal of Public Administration in the Digital Age*, *2*(2), 75–92.

https://doi.org/10.1017/jmo.2023.68 Published online by Cambridge University Press

Kalampokis, E., Tambouris, E., & Tarabanis, K. A. (2011). A classification scheme for open government data: Towards linking decentralised data. *International Journal of Web Engineering and Technology*, *6*(3), 266–285.

Kaplan, S. N., Klebanov, M. M., & Sorensen, M. (2012). Which CEO characteristics and abilities matter? *The Journal of Finance*, *67*(3), 973–1007.

Kassen, M. (2013). A promising phenomenon of open data: A case study of the Chicago open data project. *Government Information Quarterly*, *30*(4), 508–513.

Khayer, A., Bao, Y., & Nguyen, B. (2020). Understanding cloud computing success and its impact on firm performance: An integrated approach. *Industrial Management and Data Systems*, *120*(5), 963–985.

Koziol-Nadolna, K. (2020). The role of a leader in stimulating innovation in an organization. *Administrative Sciences*, *10*(3), 59.

Lee, G., & Kwak, Y. H. (2012). An open government maturity model for social media-based public engagement. *Government Information Quarterly*, *29*(4), 492–503.

Leviäkangas, P., & Molarius, R. (2020). Open government data policy and value added – Evidence on transport safety agency case. *Technology in Society*, *63*, 101389.

Liang, Y. K., Wang, W. J., Dong, K. X., Zhang, G. J., & Qi, G. J. (2021). Adoption of mobile government cloud from the perspective of public sector. *Mobile Information Systems*, *2021*, 1–20.

Liao, S. H., Chen, C. C., Hu, D. C., Chung, Y. C., & Liu, C. L. (2017). Assessing the influence of leadership style, organizational learning and organizational innovation. *Leadership & Organization Development Journal*, *38*(5), 590–609.

Li, H., & Atuahene-Gima, K. (2002). The adoption of agency business activity, product innovation, and performance in Chinese technology ventures. *Strategic Management Journal*, *23*(6), 469–490.

Magalhaes, G., & Roseira, C. (2020). Open government data and the private sector: An empirical view on business models and value creation. *Government Information Quarterly*, *37*(3), 101248.

Mei, C. (2018). A study on the value of open government data: Connotation, evaluation and practice. *Library*, *288*(9), 27–32.

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, *57*(2), 103169.

Nitzl, C., Roldan, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management and Data Systems*, *116*(9), 1849–1864.

The People's Government of Zhejiang Province. (2020). *Zhejiang Open Data Innovation and Application Competition*. Retrieved August 24, 2022, from https://odic.zjzwfw.gov.cn/.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891.

Ragu-Nathan, B. S., Apigian, C. H., Ragu-Nathan, T., & Tu, Q. (2004). A path analytic study of the effect of top management support for information systems performance. *Omega*, *32*(6), 459–471.

Reb, J., Narayanan, J., & Chaturvedi, S. (2014). Leading mindfully: Two studies on the influence of supervisor trait mindfulness on employee well-being and performance. *Mindfulness*, *5*(1), 36–45.

Rodríguez, N. G., Pérez, M. J. S., & Gutiérrez, J. A. T. (2008). Can a good organizational climate compensate for a lack of top management commitment to new product development? *Journal of Business Research*, *61*(2), 118–131.

Rosenbloom, R. S. (2000). Leadership, capabilities, and technological change: The transformation of NCR in the electronic era. *Strategic Management Journal*, *21*(10-11), 1083–1103.

Seifert, J. W. (2004). Data mining and the search for security: Challenges for connecting the dots and databases. *Government Information Quarterly*, *21*(4), 461–480.

Shao, Z., Feng, Y. Q., & Hu, Q. (2017). Impact of top management leadership styles on ERP assimilation and the role of organizational learning. *Information & Management*, *54*(7), 902–919.

Shin, S. J., & Zhou, J. (2003). Transformational leadership, conservation, and creativity: Evidence from Korea. *Academy of Management Journal*, *46*(6), 703–714.

Slevin, D. P., & Covin, J. G. (1997). Strategy formation patterns, performance, and the significance of context. *Journal of Management*, *23*(2), 189–209.

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology*, *13*, 290–312.

Sohal, S., Moss, A., & Ng, L. (2001). Comparing IT success in manufacturing and service industries. *International Journal of Operations and Production Management*, *21*(1/2), 30–45.

Susha, I., Grönlund, Å., & Janssen, M. (2015). Driving factors of service innovation using open government data: An exploratory study of entrepreneurs in two countries. *Information Polity*, *20*(1), 19–34.

Talke, K., Salomo, S., & Rost, K. (2010). How top management team diversity affects innovativeness and performance via the strategic choice to focus on innovation fields. *Research Policy*, *39*(7), 907–918.

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350.

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *Processes of technological innovation*. UK: Lexington Books.

Vaccaro, I. G., Jansen, J. J. P., Van Den Bosch, F. A. J., & Volberda, H. W. (2012). Management innovation and leadership: The moderating role of organizational size. *Journal of Management Studies*, *49*(1), 28–51.
Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356–365.
Wang, H.-J., & Lo, J. (2016). Adoption of open government data among government agencies. *Government Information Quarterly*, *33*(1), 80–88.
Wang, H.-J., & Lo, J. (2020). Factors influencing the adoption of open government data at the firm level. *IEEE Transactions on Engineering Management*, *67*(3), 670–682.
Weiner, B. J., Shortell, S. M., & Alexander, J. (1997). Promoting clinical involvement in hospital quality improvement efforts: The effects of top management, board, and physician leadership. *Health Services Research*, *32*(4), 491–510.
Yang, J. (2008). Unravelling the link between knowledge integration and new product timeliness. *Technology Analysis & Strategic Management*, *20*(2), 231–243.
Yukl, G., Gordon, A., & Taber, T. (2002). A hierarchical taxonomy of leadership behavior: Integrating a half century of behavior research. *Journal of Leadership & Organizational Studies*, *9*(1), 15–32.
Yu, C. P., Wang, Y., Li, T. C., & Lin, C. P. (2022). Do top management teams' expectations and support drive management innovation in small and medium-sized enterprises? *Journal of Business Research*, *142*, 88–99.
Zhang, N., Zhao, X., Zhang, Z., Meng, Q., & Tan, H. (2017). What factors drive open innovation in China's public sector? A case study of official document exchange via microblogging (ODEM) in Haining. *Government Information Quarterly*, *34*(1), 126–133.
Zhao, Y., & Fan, B. (2018). Exploring open government data capacity of government agency: Based on the resource-based theory. *Government Information Quarterly*, *35*(1), 1–12.
Zhao, Y., & Fan, B. (2021). Effect of an agency's resources on the implementation of open government data. *Information & Management*, *58*(4), 103465.
Zhou, M., Wang, Y., Jiang, H., Li, M., & Li, G. (2023). How leadership influences open government data (OGD)-driven innovation: The mediating role of organizational commitment. *Sustainability*, *15*(2), 1219.
Zuiderwijk, A., Helbig, N., Gil-García, J. R., & Janssen, M. (2014). Special issue on innovation through open data – A review of the state-of-the-art and an emerging research agenda: Guest editors' introduction. *Journal of Theoretical and Applied Electronic Commerce Research*, *9*(2), 1–13.
Zuiderwijk, A., & Janssen, M. (2014). Open data policies, their implementation and impact: A framework for comparison. *Government Information Quarterly*, *31*(1), 17–29.
Zuiderwijk, A., Janssen, M., Poulis, K., & Kaa, G. V. D. (2015). Open data for competitive advantage: Insights from open data use by companies. *Proceedings of the 16th Annual International Conference on Digital Government Research*, 79–88
Zurada, J., & Karwowski, W. (2011). Knowledge discovery through experiential learning from business and other contemporary data sources: A review and reappraisal. *Information Systems Management*, *28*(3), 258–274.

Cite this article: Wang, Y., Jiang, H., Han, D., Zhou, M., and Li, G. (2024). How top leaders' support affects open government data (OGD)-driven innovation capacity of firms: Based on the TOE framework perspective. *Journal of Management & Organization*, 1–17. https://doi.org/10.1017/jmo.2023.68