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Dynamic capability deployment: The roles of dominant logic and international entrepreneurial orientation

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ABSTRACT

To identify factors that drive firms to deploy dynamic capabilities (DCs) more effectively and efficiently than others in changing international environments, this study explores how an explorative versus exploitative dominant logic might affect the technical fitness of firms' DC deployment, conditional on the level of international entrepreneurial orientation (IEO). Empirical findings from Chinese firms suggest that beyond the effect of the dominant logic on the effectiveness and efficiency of their DC deployment, firms' IEO has relevant impacts on this relationship.

1. Introduction

In a rapidly changing and globalized business landscape, firms face the perpetual challenge of capitalizing on new opportunities to ensure sustained success. To navigate this turbulent international environment, firms rely on their dynamic capability (DC) deployment—the capacity to sense and seize emerging opportunities while adapting their existing resources and capabilities to align with these new prospects. The performance of this DC deployment is defined by its technical fitness, as measured by its efficiency and effectiveness in driving the intended outcomes (Helfat & Peteraf, 2009), which means capitalizing on new opportunities within an international context.

Extant research in the realm of DCs has predominantly revolved around cognitive perspectives, which posit that a firm's DC deployment is a product of a "learning process involving a deliberate acquisition and manipulation of mental representation" (Nayak et al., 2020, p. 282). This line of inquiry delves into the intricate processes and routines wherein DCs are embedded and made effective, emphasizing psychological and cognitive microfoundations (Eggers & Kaplan, 2013; Hodgkinson & Healey, 2011). This research sheds light on the idiosyncrasies of DC deployment, attributing variations in performance to differences in a firm's inferential reasoning—a process shaped by the cognitive framework of the firm and its top managers. Kor and Mesko (2013) emphasize the significance of a firm's dominant logics (Prahalad & Bettis, 1986) in elucidating the idiosyncrasies of DC deployment.

Nevertheless, despite acknowledging the role of non-cognitive microfoundations in DC deployment (Nayak et al., 2020), there remains a notable dearth of research clarifying the impact of such non-cognitive microfoundations and the intricate interplay between cognitive and non-cognitive factors in shaping the performance of DC deployment. To address this gap in the existing literature, our study considers the concept of international entrepreneurial orientation (IEO) as a representative non-cognitive microfoundation and investigates its influence on the relationship between a firm's dominant logics—as a cognitive microfoundation—and a firm's DC deployment performance. Accordingly, we pose two research questions: (1) How do a firm's dominant logics affect the performance of DC deployment?; and (2) How might IEO influence this relationship?

We contend that dominant logics represent a cognitive microfoundation that plays a pivotal role in shaping a firm's DC deployment, impacting its efficiency and effectiveness. Dominant logics, akin to a firm's DNA, represent deeply ingrained cognitive structures that

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determine how firms formulate their strategic actions (Prahalad & Bettis, 1986). Each dominant logic is highly contextualized, such that its role varies across environmental contexts (von Krogh et al., 2000). For this study, we predict that the ways such logics guide firms' DC deployment, to adapt to or produce environmental changes, differ. Moreover, firms can exhibit multiple dominant logics concurrently (e.g., explorative, exploitative), allowing them to leverage them when competing in diverse environments, such as new or international markets (Bettis et al., 2015). Building on Nayak et al.'s (2020) conceptualization of non-cognitive microfoundations of DC deployment, we posit that the impacts of explorative and exploitative dominant logics are conditioned by a firm's IEO, a non-cognitive microfoundation acquired in the institutional context in which the firm was founded and imprinted as its enduring non-cognitive substrate.

To empirically assess our arguments, we draw upon survey data collected from 548 Chinese firms in China founded before and after 2001 when China first opened its economy to foreign business and joined the World Trade Organization (WTO). Drawing on data about firms from a transitioning economy offers a rich context to explore the influences of IEO, given the unique dynamics and evolving institutional landscape of such economies (Kim et al., 2010; Lau et al., 2002). As these economies undergo a multistage institutional change process, with each stage reflecting a different institutional context (Greenwood et al., 2002; Hoffman, 1999; Peng, 2003), it has a profound impact on shaping the firms' IEO in distinct ways. Our study distinguishes between firms founded before (i.e., low IEO) and after (i.e., high IEO) China's economic reform and examines how low versus high IEO, shaped by the institutional context of their founding, affects the impacts of explorative and exploitative dominant logics on DC deployment performance, particularly in terms of their effectiveness and efficiency.

In turn, this research makes several noteworthy contributions. First and foremost, it advances microfoundational research on DC deployment by examining the intertwined impacts of both cognitive and non-cognitive microfoundations, providing a more comprehensive understanding to elucidate the idiosyncrasies in the effectiveness and efficiency of DC deployment. We consider a firm's explorative and exploitative dominant logics as the cognitive microfoundations of its DC deployment and IEO as a non-cognitive one. While we already understand that DCs are especially critical in explaining performance differentials for firms operating in international environments (Lessard et al., 2016; Teece, 2014), with this study we further outline the role of IEO as a non-cognitive mircrofoundation of DC deployment that can shape DC deployment performance, ultimately as a precursor to firm performance.

Second, our study is a first attempt to assess the simultaneous impacts of a firm's cognitive and non-cognitive microfoundations in explaining DC deployment performance. Our findings indicate that this performance can rest on both cognitive (Eggers & Kaplan, 2013; Hodgkinson & Healey, 2011) and non-cognitive microfoundations (Nayak et al., 2020). Cognitive microfoundations, in the form of a firm's dominant logic as operationalized in this study, may impact DC deployment performance, but not inevitably. Whereas an explorative dominant logic is fundamentally aligned with the nature of DC deployment and, hence, strengthens its performance, the same does not apply an exploitative dominant logic which must be enabled, as we show, by IEO to enhance DC deployment performance. Therefore, cognitive and non-cognitive microfoundations that are aligned with the nature of DC deployment (e.g., explorative dominant logic and prevalent EIO) are beneficial to and improve its performance, but those that are inharmonious (e.g., exploitative dominant logic and lacking IEO) by themselves can be detrimental and may diminsh its performance. Although cognitive microfoundations may direct a firm's attention in its DC deployment, this deployment is not solely shaped by what it knowing pays attention to but also by its disposition such as its IEO.

Thirdly, it highlights the significance of distinguishing between the effectiveness and efficiency of DC deployment and underscores the differential impact of dominant logics and IEO on these two aspects of technical fitness. To the best of our knowledge, this study is among the first, if not the first, to empirically examine these impacts. We establish how a firm's explorative and exploitative dominant logics exert differential effects on the DCs' technical fitness, especially in light of a firm's IEO. The prevalence of these dominant logics alters the quality, speed (i.e., effectiveness), and costs (i.e., efficiency) of DC deployment.

2. Theoretical background

2.1. Dynamic capability deployment performance

DCs are critical in explaining performance differentials for firms operating in international environments (Fredrich et al., 2022; Lessard et al., 2016; Teece, 2014); they reflect "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece et al., 1997, p. 516). To maintain a sustainable competitive advantage in rapidly changing environments, firms need to create, strengthen, and renew their resource base continually (Teece et al., 1997). Helfat et al. (2007) propose two measures of the changes achieved by deploying DCs: evolutionary fitness and technical fitness. Evolutionary fitness defines "how well a dynamic capability enables an organization to make a living by creating, extending, or modifying its resource base" which is determined by the extent to which capabilities match the environment in which a firm operates (Helfat et al., 2007, p.7). Technical fitness captures an internal measure of capability performance as it reflects "how effectively a capability performs its intended function when divided by its cost" (Helfat et al., 2007, p. 7). Thus, technical fitness captures two dimensions: quality of a capability and cost of capability development and use (Helfat et al., 2007). In turn, DC deployment should support both doing the right thing (evolutionary fitness) and doing things right (technical fitness) (Ambrosini & Bowman, 2009). In this way, high-quality DC deployment produces evolutionary fitness for the firm and technical fitness for the firm's ordinary capabilities. Yet, beyond considering technical fitness for ordinary capabilities only, DC deployment itself should be evaluated in terms of its technical fitness.

In addition to considering the quality of DC deployment (i.e., establishing evolutionary and technical fitness for the firm), Wilden et al. (2019) and Zott (2003) further highlight the important roles of timing, or more suitably speed, in determining the *effectiveness* of DC deployment. Another dimension of technical fitness is the cost of financial and human resources in efforts concerning the use of DCs in producing evolutionary fitness for the firm and technical fitness of the firm's ordinary capabilities, which determines the *efficiency* of DC deployment. Accordingly, we capture the two dimensions of technical fitness—effectiveness and efficiency—of DC deployment with three performance measures: (1) quality and (2) speed of DC deployment (effectiveness) and (3) cost to enable the deployment of DCs (efficiency).

2.2. Dominant logics as a cognitive microfoundation of DC deployment

A firm's dominant logic characterizes "the way in which managers conceptualize the business and make critical resource allocation decisions" (Prahalad & Bettis, 1986, p. 490). Managers who work together over time develop a shared dominant logic that drives collective decisions and actions (Kor & Mesko, 2013). As an organizational-level phenomenon, dominant logic is embedded in a firm's routines, procedures, and resource commitments (von Krogh & Roos, 1996, pp. 235–236). Hence, dominant logics play a significant role in determining a firm's capability deployment (Eggers & Kaplan, 2013) and current and future behavior in a path-dependent fashion (Bettis & Prahalad, 1995; Bettis & Wong, 2003; von Krogh et al., 2000). When a firm encounters change, the dominant logic anchors how the firm defines its role and subsequent DC deployment to deal with emerging problems (Eggers & Kaplan, 2013). Accordingly, dominant logics act as a cognitive microfoundation which determines the effective and efficient deployment of

DCs.

The attention-based view (ABV), which argues that "what decision-makers do depends on what issues and answers they focus their attention on" (Ocasio, 1997, p. 188), offers a theoretical basis to further substantiate how a firm's dominant logic drives its DC deployment. Because a firm's dominant logic represents a collective cognitive map and strategic mindset that determines the firm's focus (Kor & Mesko, 2013), it also directs the firm's attention to those foci. In other words, the dominant logic functions as a filter that screens out unneeded or unwanted information so that the firm prioritizes those data deemed relevant, according to its dominant logic (Bettis & Prahalad, 1995). While this selectivity screens out peripheral environmental stimuli (Levinthal & March, 1993), it also enhances the level of attentional intensity (Li et al., 2013) and degree of "mindfulness" applied when dealing with focal issues (Levinthal & Rerup, 2006; Weick & Sutcliffe, 2006). Among the vast information available to most firms, applying attentional intensity increases the likelihood that the firm can recognize and make use of relevant information that otherwise might be ignored, if it fails to align with the firm's focus (Shepherd et al., 2017). That is, attentional intensity helps the firm leverage filtered information, in accordance with its dominant logic when deploying DCs.

Bettis et al. (2015) distinguish two orientations of dominant logic: explorative and exploitative orientation. The former encourages firms to search, innovate, and experiment, whereas the latter drives firms to seek incremental improvements to its existing operational capabilities (March, 1991). Multiple dominant logics can coexist simultaneously within a single firm (Bettis et al., 2015). When explorative and exploitative logics coexist, they might create a complementary relationship, or a competitive relationship might arise that requires the firm to make a trade-off (Tarba et al., 2020). On the one hand, an exploitative orientation directs firms to adapt quickly to the environment, yielding more immediate change with lesser risk than an explorative orientation would (Sethi & Sethi, 2009). However, an excessive focus on exploitation with too little exploration may result in excessive focus on short-term benefits and, thus, limit the realization of long-term opportunities and investment (Auh & Menguc, 2005). It can also create organizational inertia (Katila & Ahuja, 2002; Kyriakopolos & Moorman, 2004), which inhibits firms' responsiveness to environmental change (Levinthal, 1991). On the other hand, an explorative orientation drives firms to take bold moves and develop new technologies and products (Levinthal & March, 1993). Hence, an excessive emphasis on exploration can quickly become costly as it involves heightened risks and demands more time for outcomes to materialize (Auh & Menguc, 2005). Although a dominant logic is acknowledged as a firm's DNA which shapes its capability deployment (Eggers & Kaplan, 2013), our understanding about the effects of explorative and exploitative dominant logics on DC deployment performance remains very limited.

2.3. International entrepreneurship orientation as a non-cognitive microfoundation of DC deployment

The concept of entrepreneurial orientation can be traced back to Mintzberg's (1973) theorization of an entrepreneurial strategy-making mode characterized by the active search for new opportunities in uncertain environments in which potential dramatic growth can be realized. Entrepreneurial orientation is measured by the qualities of risk-taking, innovation, and proactive behavior (Covin & Wales, 2012). In relation to entrepreneurial orientation, Freeman and Cavusgil (2007, p. 3) define IEO as "the behavior elements of a global orientation and captures top management's propensity for risk-taking, innovativeness, and proactiveness." As such, IEO represents a disposition toward entrepreneurial behavior and encapsulates the same conceptualization of entrepreneurial orientation which concerns risk-taking, innovative and proactive behaviors of firms, providing a reflection of the values, tendencies, and orientations of its members (Covin & Miller, 2014).

Through a process of organizational imprinting, a firm's orientation emerges from the instituional context in which it was established (Stinchcombe, 1965). Organizational imprinting is "a process whereby, during a brief period of susceptibility, a focal entity develops characteristics that reflect prominent features of the environment, and these characteristics continue to persist despite significant environmental changes in subsequent periods" (Marquis & Tilcsik, 2013, p. 201). A brief period of susceptibility implies a *sensitive period* (Marquis & Tilcsik, 2013), which exists at the moment of a firm's founding (Carroll & Hannan, 2004; Johnson, 2007) when the "mapping of an environmental condition onto the organization" can take place (Carroll & Hannan, 2004, p. 206). During the establishment period, founders and managers gauge the environment and seek to find a good fit, while managing the uncertainty of newness and the pressures of legitimacy (DiMaggio & Powell, 1983; Hannan & Freeman, 1977). This mapping then becomes a lasting characteristic imprinted in a firm (Baron et al., 1999; Johnson, 2007).

Due to inertia and institutionalization, organizational imprints can persist even if significant changes take place in the environment, such that "organizations are initially structured to fit the existing environment and then, because of subsequent inertia and institutionalization, continue to exhibit traces of the founding context" (Marquis & Tilcsik, 2013, p. 203). The notion of organizational imprinting, in the form of IEO, implies that organizations establish "goals and rules, coordination mechanisms, and communication channels" (Scott, 2008, p. 124), which persist because they are taken for granted and "infused with value beyond the technical requirements of the task at hand" (Selznick, 1957, pp. 16–17). For example, economies and supporting institutions that facilitate openness and internationalization legitimize entrepreneurial behavior and provide a more international entrepreneurship–oriented climate (Sebora & Li, 2006), which does not arise in more closed, less internationalized settings. Therefore, the organizationally imprinted IEO stems from the context and time when the firm was established.

The organizationally imprinted IEO represents a firm's non-cognitive substrate reflecting a disposition towards entrepreneurial behavior, thereby IEO manifests a firm's habitus. Habitus describes a "durable, transposable set of dispositions" (Bourdieu, 1990, p. 52) and provides consistency in collective actions without relying on conscious awareness and deliberate planning (Nayak et al., 2020). Habitus incorporates the active "presence of past experiences" to maintain consistency in firm behaviour (Nayak et al., 2020). Besides habitus, another fundamental aspect of a firm's non-cognitive substrate concerns its finely-honed and tacitly-transmitted empirical sensitivity to environmental affordances (Nayak et al., 2020). A firm's operating environment during its founding period shapes how it leverages environmental affordances—opportunities provided by the environment that the firm can harness in accordance with its values—to its advantage (Nayak et al., 2020). A firm idiosyncratically refines its capacity to discern environmental opportunities based on what the environment affords a firm, so-called empirical sensitivity (Nayak et al., 2020). Within diverse founding environments, a firm cultivates its distinctive empirical sensitivity to environmental affordances, exemplified in our study by variations in IEO– either low or high. While an empirical sensitivity highlights a refined attunement to environmental affordances acquired through extended interactions at the forefront, habitus refers to the collective predispositions and practices that firms cultivate as a result of these adaptive actions (Nayak et al., 2020). Once the low/high IEO imprinted in a firm becomes sedimented and incorporated into its habitus, it simultaneously enables and constrains future responsive action, including DC deployment, further clarifying the nexus of firms' international experience and their DC deployment (Tang & Gudergan, 2018).

In view of the above, firm heterogeneity is not simply dependent on its cognition (i.e., dominant logic) but also on its historically-shaped non-cognitive dispositions (i.e., imprinted low/high IEO). A firm's IEO conditions the deliberately planned guidance dominant logics provide in light of this dispositional nature. Thus, the firm's IEO can disrupt, reinforce, or impede the attention dictated by its dominant logic which guides its DC deployment. We anticipate heterogeneity in how firms embrace an explorative, exploitative, or both dominant logics (Altintas et al., 2022), but because IEO results from imprinting given the institutional contexts within which firms emerged, just a few, relatively homogenous groups of firms likely can be defined in terms of their level of IEO (e.g., firms that have a low IEO versus others that have a high IEO) in each country that has experienced certain institutional shifts. Thus, the level of IEO should condition the relationships between explorative and exploitative dominant logics and the effectiveness and efficiency (i.e., quality, speed and efficiency) of DC deployment, because a firm's behaviour, including DC deployment, is rooted in a combination of cognitive and non-cognitive micorfoundations.

3. Hypothesis development

3.1. Dominant logic and DC deployment performance

An explorative dominant logic plays a pivotal role in navigating firms through DC deployment, particularly when sensing and seizing new opportunities that necessitate a change in ordinary capabilities. This logic directs firms to challenge conventional thinking to explore emerging technologies and to experiment with novel alternatives (Atuahene-Gima & Murray, 2007), enabling them to swiftly detect and capitalize on emerging opportunities (Teece, 2007). The emphasis on flexibility in this logic (March, 1991) provides firms rapid feedback, contributing to a nuanced cognitive schema (Dane & Pratt, 2007) helping them understand better complex problems and conceive of new solutions in a timelier fashion (Gajendran et al., 2014). It also broadens firms' awareness of alternative organizational routines that can complement or substitute their existing ones (Obloj et al., 2010), enabling faster and more comprehensive responses to challenges. Thus, we argue that an explorative dominant logic enhances organizational innovation by fostering timely responses to the environment (Brown & Eisenhardt, 1995). In essence, an explorative dominant logic positively affects both the *quality* and *speed* of DC deployment.

In addition, a firm's dominant logic is formed and strengthened through organizational learning, which involves encoding past experiences into routines that guide behavior (Levitt & March, 1988). This learning process is path-dependent and self-reinforcing, with repetitive behaviors leading to the development of cognitive schemas that influence future behavior (Schreyogg & Kliesch-Eberl, 2007; Pratt, 2003), shaping a firm's attention and its DC deployment. This learning, in turn, allows firms with an explorative dominant logic—encouraging the exploration of innovative ideas and the pursuit of new opportunities (Obloj et al., 2010)—to cultivate a comprehensive knowledge base. This accumulated knowledge empowers them to adeptly sense and seize new opportunities (Cavusgil et al., 2007), consequently resulting in a concurrent reduction in costs associated with DC deployment.

On the other hand, an exploitative dominant logic directs firms to reapply existing knowledge in a new context, thereby restricting their attention from generating radically new initiatives and opportunities (Denrell & March, 2001). This logic steers firms to be discerning in their attention and, consequently, investment in new opportunities (Rowley et al., 2000). More precisely, an exploitative dominant logic directs firms to concentrate solely on familiar patterns of new opportunities within their reach, limiting the potential for radical novelty in their solutions. With an emphasis on reapplication of prior knowledge and experience (Katila & Ahuja, 2002), firms with an exploitative dominant logic likely screen out opportunities perceived as misaligned with their mainstream (Hoang & Rothaermel, 2010), inhibiting experimentation, shortening their planning horizons and disregarding a holistic environmental landscape (Levinthal & March, 1993). Consequently, this logic results in solutions to problems and busines opportunities that are less novel and lower quality. It also constraints firms' abilities and efforts in sensing and seizing new business opportunities, thereby reducing the speed of their DC deployment. Adherence to an exploitative dominant logic also contributes to cognitive inertia, heightening firms' resistance to change (Denrell & March, 2001) and impeding the timely reconfiguration of their resource base to capture new business opportunities. We hence contend that an exploitative dominant logic exerts a detrimental effect on both the *quality* and *speed* of DC deployment.

Due to the concentrated focus of an exploitative dominant logic on enhancing existing resources, it guides firms to design their business processes to leverage existing resources and capabilities instead of encouraging radical changes for novel ideas and opportunities (March, 1991). Moreover, a strong exploitative dominant logic narrows firms' attention to a restricted scope, fostering organizational inertia (Luo, 2000). It also may result in the development of core rigidities, heightening the likelihood of firms resisting change (Argyris, 1977). Building on these arguments, we posit that under an exploitative dominant logic, firms are constrained in sensing and seizing new opportunities and encounter resistance when engaging in DC deployment activities, making the DC deployment more *costly* (reducing its efficiency).

3.2. The role of IEO in the relationship between explorative dominant logic and DC deployment

As a non-cognitive microfoundation, IEO should be conducive to how an explorative dominant logic guides firms in exploring and capitalizing on new opportunities (March, 1991) through sensing and seizing activities. Firms exhibiting a high level of IEO are disposed to capitalize on trade openness and embedded opportunities (Naudé & Rossouw, 2010). This disposition reflects their empirical sensitivity, characterized by a heightened capacity to sense differences and discriminate. This sensitivity acts as an operative substrate enabling firms to excel in identifying and "orchestrating" opportunities for value creation (i.e., reconfiguring resources). In this way, a high level of IEO can strengthen the positive relationship between an explorative dominant logic and the quality of DC deployment. Because firms with a high level of IEO innovate boldly and proactively and prioritize new opportunities (Wang & Altinay, 2012), we argue that their level of IEO supports opportunity sensing and seizing processes and, thus, strengthens the positive relationship between an explorative dominant logic and the *quality* of DC deployment.

Furthermore, a high level of IEO provokes firms to identify new opportunities and emphasizes proactiveness and a willingness to experiment with new radical ideas and innovation (Miller, 1983) in response to environmental changes. The risk-taking and willingness to experiment induced through a high level of IEO trigger firms to act more promptly, enhacing the likelihood of swiftly sensing and seizing new opportunities as they arise. Building on this rationale, we posit that a high level of IEO will further strengthen the positive relationship between an explorative dominant logic and the *speed* of DC deployment.

In addition, firms with a high level of IEO are inherently inclined to embrace and support new ideas and experimentation (Wang & Altinay, 2012). The risk-taking that comes with a high level of IEO translates into more exploratory and innovative activities in response to environmental changes (Covin & Miller, 2014). While an explorative dominant logic, as discussed earlier, contributes to the reduction of the costs in DC deployment, a high level of IEO prompts firms to embrace risks and proactively experiment with new opportunities. This disposition could potentially result in higher costs of DC deployment. Taken together, we argue that a high level of IEO weakens the positive relationship between an explorative dominant logic and the *efficiency* of DC deployment. Drawing on this line of arguments, we hypothesize:

Hypothesis 1:. *The positive relationship between a firm's explorative dominant logic and the quality of its DC deployment is stronger for firms with high IEO than for those with low IEO.*

Hypothesis 2:. *The positive relationship between a firm's explorative dominant logic and the speed of its DC deployment is stronger for firms with high IEO than for those with low IEO.*

Hypothesis 3:. *The positive relationship between a firm's explorative dominant logic and the efficiency of its DC deployment is weaker for firms with high IEO than for those with low IEO.*

3.3. The role of IEO in the relationship between exploitative dominant logic and DC deployment

As firms with an exploitative dominant logic concentrate their attention to the recombination or reapplication of existing knowledge in a new context, rather than exploring for radical newness (Denrell & March, 2001), their sensing becomes limited with a more selective approach to seizing new opportunities and responding to changes in the environment. This behavior is further influenced by their level of IEO, which conditions them to either focus narrowly or widely on risk-taking and experimenting with new ideas in response to emerging opportunities.

A high level of IEO prompts firms to proactively monitor their environment, identifying new opportunities and experimenting with new, radical ideas, thus increasing the likelihood of deviating from the existing routines (Covin & Miller, 2014). These characteristics associated with a high level of IEO counterbalance the guidance of an exploitative dominant logic, which typically directs firms to remain in their comfort zone, relying heavily on local search and reapplication of existing knowledge. Thus, a high level of IEO triggers firms to explore more extensively and deeply for innovative ideas (Cheng & Huizingh, 2014), leading to more radical innovation and higher-quality sensing, seizing and reconfiguring of their resource base to capture new opportunities. In addition, the risk-taking inherent in a high level of IEO induces firms to more proactively and promptly sense and respond to changes and opportunities (Keh et al., 2007), thereby accelerating the speed of firms' DC deployment. Accordingly, we posit that a high level of EO mitigates the negative impact of an exploitative dominant logic on the *quality* and *speed* of firms' DC deployment.

Further more, the inclination towards local search and reapplication of existing knowledge, rather than exploring new alternatives, for firms with an exploitative dominant logic results in a limited knowledge set and less novel responses to changes in the environment (March, 1991), leading to increased costs when engaging DC deployment. However, the predisposition to take risks and experiment under a high level of IEO can drive firms to embrace more innovative behaviors in response to new opportunities (Covin & Wales 2019; Kraus et al., 2019). Hence, a high level of IEO enables firms with an exploitative dominant logic to counterbalance the negative effect of an exploitative dominant logic on the efficiency of DC deployment. Therefore, we posit that a high level of IEO mitigates the negative effect of a firm's exploitative dominant logic on the efficiency of DC deployment. Building upon these arguments, we propose the following hypotheses:

Hypothesis 4. *The negative relationship between a firm's exploitative dominant logic and the quality of its DC deployment is weaker for firms with high IEO than those with low IEO.*

Hypothesis 5. *The negative relationship between a firm's exploitative dominant logic and the speed of its DC deployment is weaker for firms with high IEO than those with low IEO.*

Hypothesis 6. *The negative relationship between a firm's exploitative dominant logic and the efficiency of its DC deployment is weaker for firms with high IEO than those with low IEO.*

4. Method

4.1. Sample

To test the hypotheses, we conducted a survey among firms located in China, sending it to senior managers of 3200 firms listed in an online business directory. After one phase of follow-ups and telephone calls, 589 managers agreed to participate finally with 548 valid responses, achieving a response rate of 17.13%, 'consistent with the 10–12% rate typical for mailed surveys to top executives' (Hambrick et al., 1993, p. 407; Heavey et al., 2009). We chose China as the empirical research context because firms' dominant logic is highly context relevant (von Krogh et al., 2000) and because China represents a pertinent research context for our theorized arguments. The institutional context has experienced dramatic changes (Lau et al., 2002). Since the initiation of China's economic reforms in 1978, it has progressed through three main stages: 1978–1991, 1992–2001, and 2002–present (Zhang et al., 2016). Prior to 1978, Chinese companies were prohibited from engaging in outbound foreign direct investment activities. Following Deng Xiaoping's initial reformation and open-door policy (stage 1), China's economy continued to remain primarily focused on domestic production, and the proportion of exports in China's economy was considerably lower than the global average (Naudé & Rossouw, 2010). However, after Deng Xiaoping's visited southern China in 1992 (stage 2), the country moved more quickly toward a capitalist, open market economy (Fleisher et al., 2010). In 1993, the Central Government formally announced that the goal of its reforms was to establish a socialist market economy and set up special economic zones. Around 1994, a strategic shift in the official ideology led to a complete abandonment of central planning and the adoption of a market system (Hasan et al., 2009). When in 2001, China joined the World Trade Organization (WTO), it opened its economy to foreign business and investment (Lau et al., 2002). China's membership in the WTO also spurred large inflows of foreign capital (Fan, 2011), which corresponded with a significant rise in the share of exports in the country's economy (Naudé & Rossouw, 2010). In turn, China's outward foreign direct investment grew at an average compounded rate of 66% between 2002 and 2008 (Deng, 2012). Since 2002 (stage 3), the Chinese government has introduced various laws and regulations aimed at promoting and protecting entrepreneurship, such as the Small and Medium Enterprises Promotion Law in 2003 (Lu & Tao, 2010), and it has organized entrepreneurship conferences to stimulate entrepreneurial development (Sebora & Li, 2006). Economic prosperity provides a foundation for an entrepreneurial climate (Covin & Miller, 2014), and China's economic reforms have set a strong stage for firms' international entrepreneurial environment. In turn, firms widely adopted IEO, reflecting mimetic behavior (DiMaggio & Powell, 1983).

As we have defined in Section 2.3, a firm's IEO is imprinted from firm's institutional contexts at its founding, so we can capture firms' IEO according to the institutional context in which they emerged, divided into periods: firms established between 1992 and 2001 and thus imprinted with low IEO or firms established after 2002, which thus were imprinted with high IEO. We exclude firms established before 1992 ($n = 98$), when internationalization was prohibited, and IEO did not exist among Chinese firms (Naudé & Rossouw, 2010). The resulting sample comprises 450 Chinese firms: 124 firms established in 1992–2001 and classified as low IEO and 326 firms established in 2002–2017 and classified as high IEO.

The English-language questionnaire was translated into Simplified Chinese through two rounds of translation and back-translation by seven bilingual contributors with managerial working experience and two expert translators. We pretested the Simplified Chinese questionnaire in 10 in-depth interviews with senior managers of Chinese firms to verify the items' content, clarity, and wording (DeVellis, 2003). A pilot test with 21 respondents confirmed the face validity and helped us refine the questionnaire further. We also undertook a series of tests to confirm that nonresponse bias and common method bias were not major concerns.

4.2. Measures

4.2.1. Dependent variables

Drawing on DC literature, we derived performance measures of DC deployment in the form of technical fitness which consists of (1) *effectiveness* to capture the quality and speed of DC deployment and (2) *efficiency* to capture the cost. We know of no previously published scales for measuring the effectiveness and efficiency of DC deployment, so we modified existing measures from Teece's (2007) DC framework of sensing, seizing, and reconfiguring to gauge the quality, speed, and cost of these three DC activities. Specifically, we adopt measures used by Jiao et al. (2013) and Wilden et al. (2013) to assess the quality (9 items), speed (9 items), and cost/efficiency (9 items) of a firm's DC deployment, compared with the industry average.

4.2.2. Explanatory variables

We measure a *firm's dominant logics* drawing on measures for both explorative and exploitative logics. To measure *explorative dominant logic*, we adopt four items from Atuahene-Gima and Murray (2007) and Obloj et al. (2010). We asked respondents to indicate the extent to which their firm's focus is on certain exploration activities on five-point Likert scales. Measurement of an *exploitative dominant logic* relies on four items adopted from Atuahene-Gima and Murray (2007) and Li et al. (2014), which refer to the extent to which a firm focuses on certain exploitation activities, also on five-point Likert scales. Minor modifications to the items ensure that they match the study context. Because *IEO* is driven by the institutional context in which firms were founded, we capture it by classifying firms into two founding periods: between 1992 and 2001 (low IEO) or after 2002 (high IEO).

While we do not offer hypotheses about *ordinary capabilities*, in line with prior studies (e.g., Wilden & Gudergan, 2015), we model them to assess our complex relationships within the broader nomonological framework within which they are embedded. We include technological (i.e., firms' ability to convert inputs into outputs using technology; Afuah, 2002) and marketing (i.e., firms' ability to build and maintain advantageous relationships with customers; Spanos & Lioukas, 2001) capabilities, using seven items (four for technological capabilities and three for marketing capabilities) from Wilden and Gudergan (2015).

We also include *firm performance* as a feature of the broader nomonological framework. Although often measured using actual financial performance, such data are difficult to obtain in China, where most firms are not publicly listed, nor are they legally required to provide financial statements to the public. Therefore, we use Wilden and Gudergan's (2015) measures to evaluate market performance and profitability in the previous three years. The use of subjective measures is a valid alternative when objective measures are not available (Venkatraman & Ramanujam, 1987), and they are often applied in strategy studies (e.g., Powell, 1992). Previous research also indicates high correlations between objective and subjective performance measures (Dess & Robinson, 1984).

4.2.3. Control variables

This study includes five control variables: firm size, industry, ownership, region, and environmental dynamism. *Firm size* is measured using the number of employees and sales volume (Wilden & Gudergan, 2015; Wilden et al., 2013). We take the natural logarithm to normalize this scale. We control for the effect of *operating industry* by using a dummy variable that indicates whether a firm operates in a manufacturing or service industry. *Ownership* is a dummy variable, indicating whether a firm is state-owned or non–state-owned; the type of ownership can have significant effects on firms' strategic decision-making (Bogner et al., 1996) and performance, especially in China (Peng & Luo, 2000). Peng and Luo (2000) argue that the coexistence of state-owned and non–state-owned firms is a significant feature of transitional economies. We control for *firm location* (i.e., region) to account for different levels of economic development in China. The region is captured by a dummy variable, coded for coastal versus rural areas. Finally, *environmental dynamism*, which likely triggers firms to develop and deploy DCs (Wilden & Gudergan, 2015), is measured with a three-item scale from Volberda and Van Bruggen (1997) and Heavey et al. (2009).

4.3. Common method variance

To minimize the possibility of common method variance, we adopted several techniques outlined by Podsakoff et al. (2003). First, to reduce incentives for socially acceptable answers, we assured the respondents that their answers were confidential and that there were no right or wrong responses. Second, we used different versions of the survey for different firms (e.g., varied ordering of questions). Third, the control variables were collected throughout the survey and checked, where possible, against secondary data. Any publicly listed firms in China must disclose annual reports to the public, so we compared the objective company information available for 93 participating publicly listed firms with the subjective company information from the others by running a t-test. The results indicate that the secondary company information (i.e., firm age, sales revenue, numbers of staff, industry, and ownership) is consistent with the answers to the survey.

Fourth, to determine if common method bias affected the empirical findings, we ran a full collinearity test for the inner variance inflation factor (VIF). All the inner VIF values are lower than 3.3, which suggests our model is free of common method bias (Kock, 2015). Fifth, we used Harman's single-factor test and entered the research variables into a principle component factor analysis. The results indicate that common method bias is unlikely to be a major concern (Lane et al., 2001). Sixth, we verified if the independent variables exhibited non-normally distributed endogeneity, to check for potential endogeneity that might exist in the model (Hult et al., 2018), using the Kolmogorov-Smirnov and Shapiro-Wilk test (Shapiro & Wilk, 1965) on the standardized composite scores of the independent variables: explorative and exploitative dominant logics; quality, speed, and efficiency of DC deployment; and ordinary capabilities. The composite scores of all of these variables exhibit normally distributed scores, which indicates that endogeneity is not a major concern (Hult et al., 2018).

4.4. Data Analysis

We analyzed the data with partial least squares structural equation modeling (PLS-SEM) in SmartPLS 3.2.6 (Ringle et al., 2022), with the aim to predict the joint impact of firms' dominant logics and IEO on DC deployment performance. PLS-SEM is particularly well suited as an analytical procedure, when the primary goals are theory building and the prediction of key constructs (Hair et al., 2022). Additionally, our model is rather complex including conditional effects. Again, PLS-SEM is uniquely capable of handling models with such complexity (Hair et al., 2022; Hair et al., 2023), especially in international business contexts (Richter et al., 2022).

In the first stage, we assessed the measurement invariance of composite models (MICOM). In the second stage, we used multi-group analysis (MGA) to analyze the moderating effect of IEO (Henseler & Fassott, 2010), which offers several advantages. First, MGA allows researchers to determine whether the parameters of a measurement model and/or the structural model are equivalent (i.e., invariant) across two or more groups (Chin et al., 2012). Second, it provides a validity test of the measurement model and replicability of the structural model across settings. Third, it allows for comparisons within a study (e.g., if samples taken from different sources can be combined into a single data set) (Fawcett et al., 2011). Specifically, we ran the MGA to compare two groups of firms in our sample: those with low IEO (founded between 1992 and 2001) and those with high IEO (founded after 2002). After estimating path coefficients for each group (Sarstedt et al., 2011), we analyzed the differences between them. Then to determine the significance of the differences, we conducted a permutation test. Finally, we ran a sensitivity analysis with three approaches: PLS-MGA, a parametric test, and the Welch-Satterthwait test (Hair et al., 2017).

5. Results

The PLS-SEM analysis results reveal that all measures meet the commonly suggested criteria for measurement model assessments (Hair et al., 2012). Most of the indicator loadings exceed 0.7, except for a few, which still exceed 0.6 (Hair et al., 2022), implying that all the indicators and dimensions are reliable. Constructs and dimensions exhibit high internal consistency, with composite reliability scores ranging between 0.7 and 0.95 (see Table 1).

In addition, we have evidence of convergent validity; for most of the scales, it exceeds the minimum threshold of 0.5, except that the speed and efficiency of DC deployment for firms with low IEO indicate values of 0.491 and 0.494 respectively (Table 1), which is sufficiently close to 0.5. In terms of discriminant validity, each item loads higher on its own construct than any other constructs. In line with Fornell and Larcker's (1981) criterion, the square root of the average variance extracted value for each latent variable is greater than the correlation values with all other latent variables (Tables 2–4). We also can confirm the heterotrait-monotrait (HTMT) criteria for both HTMTinference and HTMT0.85 (Tables 5–7), in further support for discriminant validity (Hair et al., 2022).

We also checked for measurement invariance to ensure the measurement model did not vary across the two groups. In detail, we used MICOM to determine if significant intergroup differences can be attributed to intergroup differences in constructs when assessing composite models. The values of Table 8 corroborate the configural, compositional invariance, which indicates full measurement invariance. The differences between groups are non-significant (permutation *p*-value > 0.05) (Hair et al., 2017).

The $PLS_{Predict}$ results also indicate that most measures in our model have good prediction quality. To obtain the Q^2 values, we conducted blindfolding and $PLS_{Predict}$ procedures in SmartPLS (Shmueli et al., 2019). Most of the Q^2 values are above 0; most PLS-SEM RMSE and PLS-SEM MAE values are less than LM RMSE and LM MAE (Table 9). The Q^2 values for most latent variables are positive, above 0 (Table 10).

On the surface, the effects of both an explorative and an exploitative dominant logic on DC deployment performance appear more favorable for firms with high IEO than for those with low IEO (see Table 11). However, a more fine-grained examination reveals that few of these differences are statistically significant. Our assessment is based on the results of the PLS-MGA. In addition, we conducted permutation, parametric and Welch-Satterthwait tests to assess the robustness of our

Table 1
Measurement Model.

Construct	Indicators	Total sample; n = 450			Firms established in 2002-2017; n = 326			Firms established in 1992-2001; n = 124		
		Loadings	Reliability	AVE	Loadings	Reliability	AVE	Loadings	Reliability	AVE
Explore DL	Explore1	0.830	0.880	0.648	0.772	0.852	0.591	0.881	0.891	0.674
	Explore2	0.853			0.840			0.879		
	Explore3	0.793			0.765			0.720		
	Explore4	0.739			0.691			0.793		
Exploit DL	Exploit1	0.683	0.861	0.611	0.617	0.830	0.554	0.820	0.891	0.674
	Exploit2	0.891			0.860			0.738		
	Exploit3	0.826			0.796			0.812		
	Exploit4	0.707			0.680			0.905		
DC deployment quality	Sen Qua1	0.739	0.929	0.594	0.645	0.906	0.519	0.834	0.945	0.658
	Sen Qua2	0.762			0.735			0.811		
	Sen Qua3	0.709			0.707			0.676		
	Sei Qua1	0.834			0.788			0.877		
	Sei Qua2	0.804			0.744			0.820		
	Sei Qua3	0.716			0.655			0.757		
	Rec Qua1	0.767			0.705			0.829		
	Rec Qua2	0.779			0.741			0.821		
	Rec Qua3	0.816			0.754			0.859		
DC deployment speed	Sen Spd1	0.744	0.927	0.585	0.668	0.896	0.491	0.836	0.953	0.695
	Sen Spd2	0.741			0.668			0.823		
	Sen Spd3	0.733			0.679			0.805		
	Sei Spd1	0.755			0.660			0.838		
	Sei Spd2	0.800			0.761			0.828		
	Sei Spd3	0.774			0.714			0.815		
	Rec Spd1	0.795			0.718			0.865		
	Rec Spd2	0.720			0.639			0.836		
	Rec Spd3	0.815			0.786			0.853		
DC deployment efficiency	Sen Co1	0.715	0.925	0.580	0.647	0.897	0.494	0.768	0.942	0.645
	Sen Co2	0.698			0.672			0.730		
	Sen Co3	0.683			0.629			0.752		
	Sei Co1	0.781			0.736			0.796		
	Sei Co2	0.780			0.733			0.803		
	Sei Co3	0.784			0.703			0.829		
	Rec Co1	0.796			0.727			0.852		
	Rec Co2	0.771			0.679			0.847		
	Rec Co3	0.836			0.785			0.843		
Ordinary capability	OC_1	0.798	0.914	0.605	0.757	0.890	0.537	0.836	0.937	0.681
	OC_2	0.759			0.718			0.823		
	OC_3	0.785			0.740			0.829		
	OC_4	0.716			0.670			0.763		
	OC_5	0.783			0.736			0.823		
	OC_6	0.779			0.719			0.851		
	OC_7	0.819			0.786			0.849		
Performance	P_1	0.899	0.941	0.799	0.877	0.934	0.779	0.932	0.951	0.830
	P_2	0.888			0.891			0.877		
	P_3	0.919			0.903			0.932		
	P_4	0.869			0.858			0.901		

Table 2
SQUARE ROOT OF AVE AND Correlation of Latent Constructs, Total Sample (n = 450).

Constructs	Explorative	Exploitative	Quality	Speed	Efficiency	OC	Performance
Explorative DL	*0.805*						
Exploitative DL	0.183	*0.781*					
Quality	0.260	0.050	*0.771*				
Speed	0.212	0.207	0.499	*0.765*			
Efficiency	0.209	0.097	0.311	0.414	*0.762*		
Ordinary Cap	0.222	0.122	0.336	0.386	0.266	*0.778*	
Performance	0.184	0.051	0.316	0.405	0.215	0.425	*0.894*

Table 3
SQUARE ROOT OF AVE AND Correlation of Latent Constructs, Firms established AFTER 2002 (n = 326).

Constructs	Explorative	Exploitative	Quality	Speed	Efficiency	OC	Performance
Explorative DL	*0.769*						
Exploitative DL	0.271	*0.744*					
Quality	0.301	0.201	*0.721*				
Speed	0.314	0.281	0.634	*0.701*			
Efficiency	0.307	0.217	0.454	0.625	*0.703*		
Ordinary Cap	0.229	0.262	0.507	0.538	0.411	*0.733*	
Performance	0.198	0.155	0.449	0.487	0.299	0.486	*0.882*

Table 4
SQUARE ROOT OF AVE AND Correlation of Latent Constructs, Firms established in 1992–2001 (n = 124).

Constructs	Explorative	Exploitative	Quality	Speed	Efficiency	OC	Performance
Explorative DL	*0.821*						
Exploitative DL	0.035	*0.821*					
Quality	0.243	-0.231	*0.811*				
Speed	0.185	0.108	0.355	*0.833*			
Efficiency	0.229	-0.119	0.288	0.225	*0.803*		
Ordinary Cap	0.293	-0.113	0.349	0.423	0.316	*0.825*	
Performance	0.154	-0.125	0.227	0.375	0.175	0.457	*0.911*

Table 5
Heterotrait-Monotrait Ratio, Total Sample (n = 450).

Constructs	Explorative	Exploitative	Quality	Speed	Efficiency	OC
Explorative DL						
Exploitative DL	0.220					
Quality	0.297	0.082				
Speed	0.245	0.200	0.536			
Efficiency	0.241	0.096	0.336	0.456		
Ordinary Cap	0.257	0.118	0.358	0.413	0.280	
Performance	0.213	0.070	0.338	0.440	0.231	0.466

Table 6
Heterotrait-Monotrait Ratio, Firms established AFTER 2002 (n = 326).

Constructs	Explorative	Exploitative	Quality	Speed	Efficiency	OC
Explorative DL						
Exploitative DL	0.341					
Quality	0.367	0.215				
Speed	0.385	0.290	0.711			
Efficiency	0.368	0.234	0.512	0.716		
Ordinary Cap	0.283	0.288	0.567	0.603	0.458	
Performance	0.239	0.180	0.499	0.548	0.332	0.547

results.

The effects of an explorative dominant logic on the quality, speed, and efficiency of DC deployment emerge as positive and significant for firms, irrespective of the level of IEO. While the positive relationships between an explorative dominant logic and the quality, speed, and efficiency of DC deployment appear stronger for firms with high IEO than those with low IEO (Table 11), permutation, parametric, and Welch-Satterthwait tests reveal no significant differences in these relationships when comparing firms with a high versus a low IEO (Tables 12 and 13). Hence, we do not have support for H1, H2 and H3.

The results of the MGA (Table 11) suggest that the relationship between an exploitative dominant logic and the quality of DC deployment is negative and significant for firms with low IEO ($\beta = -0.240$, $p < 0.05$), consistent with our prediction in H4. But the relationship between an exploitative dominant logic and the quality of DC deployment is positive and significant for firms with high IEO ($\beta = 0.129$, $p < 0.05$), contrary to our prediction in H4. Given we are to test the moderation effect of IEO on the relationship between and exploitative dominant logic and the

Table 7
Heterotrait-Monotrait Ratio, Firms established 1992–2001 (n = 124).

Constructs	Explorative	Exploitative	Quality	Speed	Efficiency	OC
Explorative DL						
Exploitative DL	0.086					
Quality	0.258	0.219				
Speed	0.195	0.120	0.355			
Efficiency	0.245	0.131	0.294	0.234		
Ordinary Cap	0.312	0.152	0.355	0.436	0.321	
Performance	0.168	0.160	0.229	0.390	0.185	0.486

Table 8
Measurement Invariance (MICOM) Test.

Compositional invariance	Correlation	95% Confidence interval	Permutation p-value
Explorative DL	0.993	[0.982, 1.000]	0.325
Exploitative DL	0.940	[0.664, 1.000]	0.266
DC deployment quality	0.996	[0.995, 1.000]	0.061
DC deployment speed	0.997	[0.996, 1.000]	0.097
DC deployment efficiency	0.998	[0.993, 1.000]	0.584
Ordinary capabilities	0.999	[0.997, 1.000]	0.714
Firm performance	1.000	[0.998, 1.000]	0.792
Composite	Mean difference 2002-2017 to 1992-2001	95% Confidence interval	Permutation p-value
Explorative DL	-0.191	[− 0.215, 0.231]	0.080
Exploitative DL	-0.104	[− 0.205, 0.219]	0.288
DC deployment quality	-0.205	[− 0.229, 0.215]	0.064
DC deployment speed	-0.214	[− 0.216, 0.196]	0.051
DC deployment efficiency	-0.134	[− 0.220, 0.201]	0.220
Ordinary capabilities	-0.198	[− 0.204, 0.194]	0.060
Firm performance	-0.115	[− 0.211, 0.205]	0.268
Composite	Variance difference 2002-2017 to 1992-2001	95% Confidence interval	Permutation p-value
Explorative DL	0.034	[− 0.311, 0.316]	0.198
Exploitative DL	-0.152	[− 0.279, 0.299]	0.460
DC deployment quality	-0.361	[− 0.322, 0.348]	0.208
DC deployment speed	-0.591	[− 0.244, 0.300]	0.098
DC deployment efficiency	-0.499	[− 0.258, 0.311]	0.304
Ordinary capabilities	-0.342	[− 0.261, 0.310]	0.152
Firm performance	-0.327	[− 0.250, 0.283]	0.358

Table 9
PLS PREDICT 1.

	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
OC1	0.026	1.033	0.845	1.026	0.836
OC2	0.036	0.943	0.812	0.93	0.768
OC3	0.029	1.05	0.881	1.035	0.848
OC4	0.009	0.979	0.819	0.988	0.798
OC5	0.027	0.847	0.681	0.854	0.679
OC6	0.023	0.899	0.749	0.904	0.738
OC7	0.025	1	0.816	0.994	0.797
PF1	0.004	1.019	0.815	1.008	0.795
PF2	0.005	1.076	0.882	1.06	0.85
PF3	-0.007	1.026	0.835	1.012	0.814
PF4	-0.023	1.081	0.908	1.076	0.903
recon cost1	0.015	1.037	0.834	1.055	0.839
recon cost2	0.016	0.987	0.776	0.99	0.766
recon cost4	0.031	0.981	0.792	0.994	0.792
sei cost1	0.025	0.954	0.775	0.954	0.761
sei cost2	0.023	1.01	0.826	1.024	0.813
sei cost4	0.026	1.065	0.87	1.071	0.85
sen cost1	0.017	0.889	0.737	0.901	0.739
sen cost2	0.007	0.902	0.746	0.91	0.724
sen cost4	0.02	0.952	0.794	0.975	0.814
recon quality2	0.021	1.056	0.874	1.064	0.871
recon quality3	0.027	1.037	0.843	1.049	0.854
recon quality4	0.043	0.984	0.802	1.002	0.801
sei quality1	0.042	1.015	0.823	1.025	0.811
sei quality3	0.001	1.042	0.817	1.06	0.838
sei quality4	0.032	0.992	0.817	1.009	0.818
sen quality1	0.05	0.894	0.721	0.898	0.706
sen quality2	0.034	0.934	0.753	0.95	0.756
sen quality4	0.036	0.9	0.738	0.907	0.722
recon speed1	0.017	1.021	0.85	1.026	0.818
recon speed3	0.019	1.064	0.896	1.057	0.872
recon speed4	0.029	0.966	0.799	0.979	0.793
sei speed1	0.038	1.066	0.896	1.073	0.88
sei speed2	0.048	1.042	0.859	1.056	0.856
sei speed4	0.026	1.011	0.85	1.009	0.815
sen speed1	0.042	0.898	0.739	0.906	0.717
sen speed3	0.059	0.953	0.797	0.957	0.763
sen speed4	0.027	0.944	0.788	0.962	0.793

quality of DC deployment, the results indicate the negative relationship with low IEO even changes to a positive one with high IEO. In addition, the other three tests show significant differences ($p < 0.05$; Tables 12 and 13) in the relationship between an exploitative dominant logic and the quality of DC deployment for firms with high versus low IEO.

The MGA results (Table 11) suggest a positive, insignificant relationship between an exploitative dominant logic and the speed of DC deployment for firms with low IEO ($\beta = 0.102$, $p > 0.1$) and a positive, significant relationship between an exploitative dominant logic and the speed of DC deployment for firms with high IEO ($\beta = 0.211$, $p < 0.001$). Hence, our results do not support H5.

The MGA results (Table 11) show a negative but insignificant relationship between an exploitative dominant logic and the efficiency of DC deployment among firms with low IEO ($\beta = -0.127$, $p > 0.1$). Then they reveal a positive and significant relationship between an exploitative

Table 10
PLS PREDICT 2.

	Q^2predict	RMSE	MAE
OC	0.042	0.983	0.795
PF	-0.007	1.007	0.79
Efficiency	0.035	0.987	0.785
Quality	0.054	0.978	0.743
Speed	0.059	0.974	0.778

Table 11
Significance Testing Results of Multi-group Path Coefficients.

Relationship	Path1 2002-2017	Path2 1992-2001	SD 1	SD 2	p-value 1	p-value 2
Explorative DL→Quality	0.266	0.252	0.070	0.097	0.000	0.009
Explorative DL→Speed	0.256	0.181	0.061	0.101	0.000	0.072
Explorative DL→Efficiency	0.268	0.233	0.068	0.109	0.000	0.033
Exploitative DL→Quality	0.129	-0.240	0.060	0.097	0.033	0.014
Exploitative DL→Speed	0.211	0.102	0.056	0.122	0.000	0.404
Exploitative DL→Efficiency	0.144	-0.127	0.062	0.099	0.019	0.198
Quality→Ordinary capabilities	0.267	0.181	0.065	0.082	0.000	0.027
Speed→Ordinary capabilities	0.309	0.315	0.076	0.092	0.000	0.001
Efficiency→Ordinary capabilities	0.097	0.192	0.065	0.094	0.137	0.041
OC→Firm performance	0.485	0.468	0.053	0.086	0.000	0.000

Table 12
Permutation Test Results.

Relationship	Path1 2002-2017	Path2 1992-2001	Difference 1-2	Confidence intervals	p-value
Explorative DL→Quality	0.266	0.252	0.014	[− 0.237, 0.253]	0.867
Explorative DL→Speed	0.256	0.181	0.075	[− 0.234, 0.239]	0.500
Explorative DL→Efficiency	0.268	0.233	0.035	[− 0.239, 0.241]	0.767
Exploitative DL→Quality	0.129	-0.240	0.369	[− 0.247, 0.306]	0.016
Exploitative DL→Speed	0.211	0.102	0.109	[− 0.235, 0.385]	0.300
Exploitative DL→Efficiency	0.144	-0.127	0.271	[− 0.249, 0.265]	0.046
Quality→Ordinary capabilities	0.267	0.181	0.086	[− 0.225, 0.205]	0.414
Speed→Ordinary capabilities	0.309	0.315	-0.007	[− 0.264, 0.269]	0.953
Efficiency→Ordinary capabilities	0.097	0.192	-0.096	[− 0.260, 0.236]	0.474
OC→Firm performance	0.485	0.468	0.017	[− 0.200, 0.193]	0.879

dominant logic and the efficiency of DC deployment for firms with high IEO ($\beta = 0.144$, $p < 0.05$). Here again, all four tests (Tables 12 and 13) reveal significant differences between firms with high versus low IEO regarding the relationship between an exploitative dominant logic and the efficiency of DC deployment. However, albeit interesting, these results are not consistent with the prediction made in H6.

Table 13
Multigroup Results Across Methods.

Relationship	Permutation p-value 2002-2017 to 1992-2001	PLS-MGA p-value	Parametric test p-value	Welch-Satterthwait test p-value
Explorative DL→Quality	0.867	0.455	0.911	0.904
Explorative DL→Speed	0.500	0.260	0.520	0.523
Explorative DL→Efficiency	0.767	0.403	0.788	0.787
Exploitative DL→Quality	0.016	0.008	0.001	0.002
Exploitative DL→Speed	0.300	0.213	0.351	0.415
Exploitative DL→Efficiency	0.046	0.015	0.021	0.021
Quality→Ordinary capabilities	0.414	0.201	0.460	0.408
Speed→Ordinary capabilities	0.953	0.523	0.960	0.955
Efficiency→Ordinary capabilities	0.474	0.799	0.427	0.403
OC→Firm performance	0.879	0.438	0.867	0.867

6. Discussion and implications

This study pertains to the role of IEO in shaping the relationship between (explorative and exploitative) dominant logics and DC deployment performance (effectiveness and efficiency). The findings extend an understanding of the factors contributing to technical fitness in DC deployment. The explorative and exploitative dominant logics have different impacts on the effectiveness and efficiency of DC deployment, and these relationships are partially conditional on firms' IEO.

We predicted that a joined consideration of cognitive (i.e., dominant logic) and non-cognitive (i.e., IEO) microfoundations enables a better prediction of differences in firms' DC deployment performance, helping clarify the determinants of the effectiveness and efficiency of firms' DC deployment. Our findings suggest that firms with high levels of IEO generally experience a positive influence of their dominant logics—both explorative and exploitative ones—on their DC deployment, irrespective of whether seeking to achieve DC deployment effectiveness or efficiency. However, more interesting are our nuanced findings, especially in light of our theorizing.

First, while we reasoned that both cognitive and non-cognitive microfoundations would matter in clarifying DC deployment performance, the extent to which either cognitive or non-cognitive microfoundations explain differences in DC deployment performance appears dependent on context. That is, DC deployment performance relies on either a high level of IEO (i.e., a non-cognitive microfoundation) *or* an explorative dominant logic (i.e., a cognitive microfoundation). The results pertaining to the performane implications of a firm's explorative dominant logic demonstrate that, irrespective of the level of IEO, as this logic manifests more strongly DC deployment performance strengthens in terns of both its effectiveness and efficiency. Hence, our findings suggests that a firm's cognitively defined explorative dominant logic trumps its non-cognitively expressed IEO. We however note that, albeit not significantly different, the magnitude of impacts of the explorative dominant logic appears marginally greater, hinting to a possible interplay whereby firms that simultaneously exhibit a high level of IEO may better leverage this dominant logic.

This conjecture becomes a reasonable proposition when unpacking the role of IEO in the context of firms exhibiting an exploitative dominant logic. Our findings reveal that the relationship between this logic and DC deployment performance is positive when firms simultaneously display a high level of IEO, but it is negative or not significant when displaying a low level of IEO. This implies that a high level of IEO is a necessary boundary condition for an exploitative dominant logic to enhance DC deployment performance. While we hypothesized that this logic would reduce DC deployment performance, this is only the case for firms with a low level of IEO and then only for DC deployment quality and efficiency. Thus, IEO, as a non-cognitive microfoundation can outdo, rather than just weaken as predicted, the negative impacts of an exploitative dominant logic, creating a positive impact.

Together, these findings lend support to the notion that DC deployment performance rests on both cognitive (Eggers & Kaplan, 2013; Hodgkinson & Healey, 2011) and non-cognitive microfoundations (Nayak et al., 2020). Cognitive microfoundations, in the form of a firm's dominant logic as operationalized in this study, can determine DC deployment performance, but not necessarily. While an explorative dominant logic is intrinsically aligned with the nature of DC deployment and, hence, strengthens its performance (in accordance with the prediction of our underlying main effects), the same is not the case for an exploitative dominant logic (again, in accordance with the prediction of our underlying main effects) which must be enabled by a high level of IEO to drive DC deployment performance. Therefore, in the context of DC deployment, cognitive and non-cognitive microfoundations that are aligned with the nature of this deployment (e.g., explorative dominant logic and prevalent EIO) are conducive to and strengthen its performance, whereas those that are incongruous (e.g., exploitative dominant logic and lacking IEO) by themselves can be obstructive and may weaken its performance. While a low level of EIO appears to not diminish the beneficial impact of an explorative dominant logic, it appears to support the detrimental impact of an exploitative dominant logic. Therefore, although a firm's dominant logic directs its attention to perceive information relevant to the dominant logic (Bettis & Prahalad, 1995), its DC deployment is shaped not only by what it consciously perceives but also by its disposition which may be the result of imprinting. Accordingly, rather than solely responding to change in deliberate ways, DC deployment may be unintentional (Nayak et al., 2020), induced through IEO in our study.

Therefore, IEO plays an important role in better understanding how DCs enable firms to compete and achieve performance advantages. We already know that DCs are especially critical in explaining performance differentials for firms operating in international environments (Lessard et al., 2016; Teece, 2014). With this study we further outline the role of IEO as a non-cognitive mircrofoundation of DC deployment that can shape DC deployment performance, ultimately as a precursor to firm performance.

7. Conclusion

Our study starts clarifying the intertwined roles of cognitive and non-cognitive microfoundations in DC deployment performance. It reveals their impacts in consideration of the effectiveness and efficiency of DC deployment. While our study operationalized cognitive microfoundations in terms of a firm's explorative and exploitative dominant logics, and non-cognitive microfoundations as IEO, further research can consider other ways of operationalizing these two types of microfoundations. For instance, Wilden and Gudergan (2017) study the role of a firm's *service dominant logic* in DC deployment but their work can be refined by further unpacking the cognitive versus non-cognitive conceptualization. Moreover, Maghzi et al. (2023) clarify proactive DC deployment such that further research could contrast proactive and reactive DC deployment to better understand the ways dominant logics and IEO shape such different ways of deploying DCs. Also, all our data come from firms based in China, which represents an appropriate setting for studying organizational imprinting, due to the existence of clearly different institutional contexts into which firms were born. But more data about firms from other countries would help generalize the findings. Furthermore, our data are cross-sectional, which does not allow for analyses of stability over time. We encourage continued studies to collect longitudinal data and delve deeper into how differences in firms' imprinting might lead to differences in the effective and efficient deployments of their DC. Then, while we suggest that IEO can be measured by considering the imprinting from the institutional context into which a firm has been born, alternative approaches such as a survey-based measurement can be considered. Finally, further research can aim to reveal configurations of firms' dominant logics and their IEO that may correspond to equifinal levels of DC deployment (applying configurational analysis such as fsQCA: Gelhard et al., 2016) and to identify necessary levels of dominat logics and IEO to acieve certain DC deployments (applying NCA: Richter et al. 2022).

Data Availability

Consideration will be given to making data available at request.

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