A motivation and ability perspective on engagement in emerging digital technologies: The case of Internet of Things solutions

Abstract

In this study, we advance two mechanisms that lead firms to engage in emerging digital technologies, namely, the dominant coalition's motivation and its ability to deploy the resources needed to pursue such motivation. Building on the performance and strategic development, and on board capital literature streams, we construe prior economic performance as a proxy of the firm's motivation, and human and social board capital as proxies of the firm's ability, analyzing their effect on adding emerging digital technologies, such as Internet of Things solutions, to the firm's resource base. Longitudinal analyses on a panel of Fortune 500 manufacturing firms between 2002 and 2012 reveal that these mechanisms highlight two important aspects of firm influence that can shape its digital technology behavior, explaining the heterogeneity and variability in firms engaging in emerging digital technologies.

Keywords: Digitalization, Emerging Technology, Internet of Things (IoT), Prior Performance, Board Capital

“It’s easy to focus only on the core business when it’s going great, but you have to find board time to focus on growth and disruptive activities.”
Brian Goldner, Hasbro CEO, on board meetings (Hill and Davies, 2017)

Introduction

Emerging technologies pose particular challenges to incumbents (Day and Schoemaker, 2000). Indeed, these solutions fundamentally change usage patterns in a market, thus creating or changing whole industries, while rendering existing competences or business models obsolete (Day and Schoemaker, 2000). Very often, firms ignore the potential of emerging technologies, focusing on lower-risk innovations closer to the existing, engaging too late, or committing insufficient resources to emerging technologies (Day and Schoemaker, 2000; Khanagha et al., 2017).

The current socio-economic scenario is increasingly characterized by emerging digital technologies, such as mobile and cloud computing, Internet of Things (IoT), 3D printing, big data analytics, and blockchain (Rindfleisch et al., 2017), which require profound changes in industrial and organizational activities and competencies to fully leverage the opportunities that these digital technologies provide (Nambisan et al., 2017; Nathan and Rosso, 2015; Stowsky, 2004; Taalbi, 2017). Among these technologies, IoT solutions are considered a pivotal technological paradigm (Kim et al., 2017a), and as an emerging technology, has the potential to radically transform business models and whole industries. ~~IoT solutions, as in the case of RFID (Radio-Frequency Identification), significantly differ from pre-existing mature technologies in terms of the nature of technical problems as well as technical solutions, requiring substantial and sustained investments before paying off (Soares, 1997; Ahuja and Lampert, 2001)~~. IoT technologies ~~refer to a “dynamic global network infrastructure with self-configuring capabilities based on standards and interoperable communication protocols, [where] physical and virtual ‘things’ have identities and attributes and are capable of using intelligent interfaces and being integrated as an information network” (Li et al., 2015, p. 244). These digital technologies~~ allow interactions and information

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processing among physical objects (e.g., household appliances, heart monitoring implants, cars), enabling them to "understand" the world around them and giving rise to a network of interconnected elements (Bandyopadhyay and Sen, 2011; Kim et al., 2017a; Touzani et al., 2018; Whitmore et al., 2015).

IoT as an emerging technology is not only changing the inherent nature of products, but also modifying value chains and firms' internal processes, transforming business models, and in turn, changing the nature of competition and industrial structures (Iansiti and Lakhani, 2014; Porter and Heppelmann, 2014). It is estimated that by 2020, there will be around 26 billion connected physical devices, a 30-fold increase from 2009 (Gartner, 2013). This rapid growth of IoT solutions based on the availability of cheap sensors, processing solutions, ubiquitous wireless coverage, and big data analytics, offers new value generation opportunities in terms of increased business efficiency, cost savings, improved customer experience, and profits (Shin, 2017; Rymaszewska et al., 2017).

To be able to benefit from such opportunities, firms need to add IoT technologies to their technological resource base. But even in the face of promising predictions and expectations, large-scale investments in IoT are not yet prevalent (OECD, 2016), which raises the question of which factors drive organizations to engage in these emerging technologies. ~~High investment requirements paired with a high risk of failure during exploration lead to variations in firm behavior concerning their engagement in new emerging technologies (Soares, 1997; Ahuja and Lampert, 2001)~~. While some firms actively engage in adding emerging digital technologies to their resources base, others often ignore their potential, focusing on lower-risk innovations that are close to their existing knowledge and expertise (Khanagha et al., 2017). Firms often either engage too late, pursue the wrong technological path, or commit insufficient resources to emerging technologies (Day and Schoemaker, 2000). Despite prior research efforts on emerging technologies (e.g., Atzori et al., 2010; Ardito et al., 2018; Feki et al., 2013; Sheng et al., 2013; Khanagha et al., 2017), we

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To fill this gap, we distill two mechanisms from the literature, namely, the dominant coalition's motivation and its ability (Eggers and Kaul, 2018; Kotlar, De Massis, Frattini and Kammerlander, 2020) to deploy the resources needed to pursue such motivation to engage in digital technologies, such as IoT solutions. Specifically, we aim to address the following research questions: What are the mechanisms through which a dominant coalition influences the firm's engagement in emerging digital technologies? Under which conditions is such influence beneficial or detrimental to the engagement in emerging digital technologies?

Building on the performance, strategic development, and board capital literature streams, we construe prior economic performance as a proxy of a firm's motivation, and human and social board capital as proxies of a firm's ability to deploy the required resources, analyzing their effect on adding IoT solutions, as a case of emerging digital technologies, to a firm's resource base.

Indeed, prior studies largely show that *prior economic performance* explains organizations' strategic decisions (Park, 2002, 2003; Villagrasa et al., 2017), thus affecting their motivation to adopt and renew their technology base to respond to digital demands. Specifically, economically successful firms tend to be trapped in established routines and practices, thus failing to explore emerging technological paradigms (Becker, 2004; Christensen, 1997). ~~While routines are necessary to reduce uncertainty and provide stability, in times of change, they may hinder organizations from adapting or innovating.~~ At the same time, poorly performing firms tend to engage more in innovation (Billings et al., 1980) and risk-taking behavior (Greve, 1998), responding with organizational change, alternative fields of operation, and diversification. As IoT offers new growth or cost saving opportunities, it is likely that poor performance makes firms more willing to engage in such emerging technologies than those with established superior firm

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performance.

However, firms may be more or less constrained in pursuing their willingness to engage in IoT technologies (Eggers and Kaul, 2018). Thus, in our theorizing, we draw on the ability and willingness literature (e.g., Chrisman et al., 2015; De Massis et al., 2014, 2015; Kotlar et al., 2020) to distinguish between *motivation*, defined as the dominant coalition's willingness to engage in firm behavior such as patenting, and its *ability* to pursue such motivation, captured by the capability of the dominant coalition's to deploy the resources needed. In examining this ability, we specifically focus on *board capital*, reflected in the board of directors' human and social capital. Resource dependence theory indicates resource provision as the board's main function (Hillman and Dalziel, 2003; Pearce and Patel, 2017), suggesting that the board plays an important role in overcoming resource constraints by providing access to skills, expertise, and networks (Boivie et al., 2016; George et al., 2001; Khanagha et al., 2017; Ramón-Llorens et al., 2018). Board capital is a proxy of the board's ability to provide specific resources and knowledge (Hillman et al., 2000; Hillman and Dalziel, 2003) by giving advice on future strategy formulation, and enabling access to external information through their personal connections and networks (Haynes and Hillman, 2010; Huse, 2007; McNulty and Pettigrew, 2016; Westphal and Zajac, 1998; Yoo and Reed, 2015). We argue that board capital influences how constrained firms are by their prior performance in engaging in emerging IoT technologies. Specifically, we hypothesize that *board human capital*, in the form of considerable context-specific expertise and experience in the firm's current operations and industry, intensifies the effect of prior performance by limiting the directors' ability to support explorative activities. On the other hand, *board social capital*, in the form of relationships with the external environment, provides the firm with external resources, knowledge, and information outside established fields, thereby fostering exploration of more distant digital technological fields, and extenuating the limiting effects of prior performance.

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To test these hypotheses, we conducted a longitudinal analysis on a panel of 127 US manufacturing firms between 2002 and 2012. Our empirical setting reflects the dominant role of the US in IoT technology (Ardito et al., 2018) and its increasing development since 1999 (Ashton, 2009; Brock, 2001). Our findings provide support for the hypothesized relationships.

With our research, we complement prior studies on emerging technologies that focus on the typical pitfalls of established firms, their organizational challenges, and the managerial and organizational approaches that help them overcome these pitfalls (e.g., Ahuja and Lampert, 2001; Day and Schoemaker, 2000; Khanagha et al., 2013, 2017). We thus provide insights on the question of why firms vary in the adoption of entrepreneurial strategies (i.e., emerging technologies) (Ahuja and Lampert, 2001). Our motivation and ability perspective integrates two important theoretical mechanisms to understand firm behavior and its heterogeneity when considering engagement in emerging digital technologies. ~~We distill two dimensions from the literature whose variations qualify the type of influence a dominant coalition has on the firm's ambition and structure, in turn determining its ability to deploy the resources needed to pursue the willingness to engage in emerging digital technologies, particularly IoT solutions, and examining their individual effects on such engagement.~~ With our findings we also add to the literature on the implications of prior performance (Park, 2002, 2003), revealing that underperforming firms are particularly active in regenerating their resource base through engagement in emerging technologies. Finally, we extend previous efforts on the innovative implications of board structure (Hillman and Dalziel, 2003), showing that social and human board capital significantly explain differences among firms in exploring novel technological domains.

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Theory and hypotheses

The firm's technology base and emerging digital technologies

The theory of the technology-based firm offers specific insights on firms that are "reliant or based upon technology in exploiting business opportunities" (Granstrand, 1998, p. 466). It provides a conceptualization of the relationship between a firm's technological resource base and other strategic characteristics (Cantwell et al., 2004; Krammer, 2016; Lee and Kang, 2015; Miller, 2004; Natalicchio et al., 2017; Srivastava and Gnyawali, 2011). Following Pavitt (1998), technology is conceptualized as the underlying set of technological knowledge described as a firm's "'body of understanding' based on competencies in specific technological fields […] in which they patent and publish" (p. 436). ~~A firm's technology base thus includes the sum of all technical knowledge (Granstrand, 1998).~~ Especially in eras of fast changing technology paradigms (Aggarwal et al., 2017; Dosi, 1982, 1997), awareness of the significant role of the firm's technology base has grown (Corradini et al., 2016; Granstrand and Sjölander, 1990; Kim et al., 2017b). Given the salience and impact of technological change, adequate technology management processes and new technological resources are essential, since the firm's technology base (Granstrand, 1998) is found to determine its capacity to innovate (Garcia-Vega, 2006; Natalicchio et al., 2017; Pavitt, 1998). Firms tend to adapt and diversify their technological resources to build on a broader range of underlying knowledge integrated in a wide variety of increasingly complex products (Dosi et al., 2017; Lee et al., 2017; Suzuki and Kodama, 2004). Recognizing this technology-pull approach (Patel and Pavitt, 1997), firms adapt and renew their technological resources once the product architecture has undergone significant changes (Ambrosini et al., 2009; Birkinshaw et al., 2016; Brush et al., 2001; Khanagha et al., 2017). They have to adapt to emerging technologies in support of the new product architecture (Birkinshaw et al., 2018; Khanagha et al., 2014; Mendonca, 2006, 2009; Rotolo et al., 2015; Schmitt et al., 2018). In view of the widespread emergence of product digitization (Nambisan et al., 2017; Yoo et al., 2010), research indicates that firms must increasingly adapt their technology base to such development (Khanagha et al., 2017; Mendonca, 2006; Nambisan, 2017; Raisch and Birkinshaw, 2008). Indeed, digitalization, defined as the

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adoption of digital technologies to sustain new value generation (e.g., Rymaszewska et al., 2017), is deeply changing the approaches and strategies that firms adopt to develop new products (Xie et al., 2016), requiring them to enlarge their knowledge base with novel and emerging technological solutions. ~~However, an industry environment with emerging technologies is an unstable landscape characterized by new entrants, new business models, complexity, uncertainty, and high risk (Khanagha et al., 2017; Day and Shoemaker, 2000).~~

As previously discussed, IoT solutions create a variety of new business opportunities (Townsend et al., 2018). The manufacturing, banking and financial services, media and entertainment industries are experiencing a revenue increase of over 27%, 18% and 16%, respectively, thanks to the development and use of IoT technologies (EY, 2016). This impact is mirrored in terms of both revenue generation and costs savings, thereby attracting the interest of many firms. GE, for instance, is transforming its aircraft engine maintenance business toward preventive maintenance and aircraft fleet optimization (Airforce Technology, 2014); Michelin's connected products permit truck fleet managers to reduce fuel consumption and costs by paying for tires on a kilometers-driven basis (Michelin, 2017); Claas Company gives farmers advice on how to improve crop flow and minimize grain losses based on equipment usage (Claas Company, 2018); AT&T, has launched a connected car service in partnership with a number of car manufactures, such as Audi, GM, Tesla, and Volvo, offering high-speed 3G or 4G connections for a monthly subscription fee of $10. This allows vehicles to act as Wi-Fi hotspot and offer services related to remote vehicle access, diagnostics, and emergency support (AT&T, 2018); Verizon Communications is saving more than 55 million kWk annually across 24 data centers by deploying hundreds of wireless connected sensors leading to a reduction of 66 million pounds in greenhouse gasses per year (Vigilent, 2011). These examples show that emerging IoT solutions are increasingly changing how firms compete in markets by shaping their new product development strategies, moving toward business

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Commented [DMA9R8]: I actually like these eamples and would leave them. But I am fine either way servitization (Coreynen et al., 2017; Rymaszewska et al., 2017). However, despite providing new value creation opportunities, IoT solutions are characterized by high technological complexity in terms of different technologies and protocols, variety of devices (Ma, 2011), and the involvement of various actors connected in value creation activities who need to be coordinated in ecosystems (Rong et al., 2015; Dattée et al., 2018). In addition, due to their recent "emergence", IoT technologies are not yet fully standardized or modularized (Westerlund et al., 2014). Complexity combined with lacking interoperability, and security and privacy concerns, make it difficult to develop clear plans (Ardito et al., 2018) or business models (Sorescu, 2017) and assess investments in IoT technology, hence associated with high risk.

As the emerging technologies literature argues, established firms vary in the adoption of entrepreneurial strategies (Ahuja and Lampert, 2001), but it is still unclear why some firms engage in emergent technologies more than others. Established companies are typically reluctant to invest at the outset, to commit enough resources, and are less likely to persist in the face of intricacies (Day & Schoemaker, 2000). Day and Shoemaker (2000), for instance, identify four common pitfalls related to emerging technologies characterized by "technological uncertainty, ambiguous market signals, and embryonic competitive structures" (p. 10). In the face of uncertainty, incumbents often adopt the position of "wait and see". When technical hurdles are high, and when it is unclear which standard will dominate in the end, firms prefer to stick with the familiar. Indeed, established firms are less likely to search for solutions in novel and unfamiliar domains where they have little experience (Danneels, 2007; Sosa, 2009; Eggers and Kaul, 2018), since this may destroy their existing competencies. ~~When the emerging technology cannibalizes the existing business, when profit perspectives are unclear or expected returns are low, when the emergent technology does not serve the needs of existing customers, and when there is no fit with the existing business model, the risk and reluctance to fully commit are high~~. Moreover, large companies are typically

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not patient enough in the face of adversity. Khanagha et al. (2013) focus on the organizational challenges of incumbents engaging in adopting emerging technologies. They argue that existing learning routines, which tend to be efficiency-oriented, and attachment to core competences make technological change very difficult. Second, resource allocation mechanisms favor existing technologies, especially when they are "vital arteries of the organization" (Khanagha et al., 2013, p. 54), when the market position is strong, and when the new technological context requires a great deal of communication and coordination. ~~Third, an incentive system that rewards financial pay-back or shareholder value creation may also reduce the motivation to invest in emerging technologies.~~

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These studies offer valuable insights into the technology-related and organizational challenges of emerging technologies, and recommendations on how to overcome them. Khanaga et al. (2017) find that two managerial factors – managerial attention to emerging fields (as it influences resource allocation), and the ability to introduce new managerial initiatives or management innovation (e.g., the introduction of new systems, structures, processes to overcome the rigidities of established organizations) – are important enablers of exploration in emerging fields. Despite the valuable insights of these few studies on the adoption of emerging technologies, the question of why some companies are more willing and able to engage with emerging digital technologies is still not fully understood (Khanagha et al., 2017).

We advance two theoretical mechanisms that lead firms to engage in emerging digital technologies, namely, a firm's motivation and its ability to deploy the necessary resources to pursue such motivation. These two theoretical mechanisms draw on a fundamental theme in management research: the relationship between a firm's ambition and the structure that determines its ability to engage in such behavior (Chandler, 1962; Hall and Saias, 1980; Miles et al., 1978). These mechanisms have also been used to explain firm heterogeneity in the adoption of technologies

(Eggers and Kaul, 2018) as well as firm heterogeneity with respect to other innovation behaviors (e.g., Bozec & Di Vito, 2019; Chrisman et al., 2015; De Massis, Di Minin and Frattini, 2015; Kotlar et al., 2020; Rondi et al., 2019; Veider and Matzler, 2016). Drawing on the behavioral theory of the firm (Cyert and March, 1963), the motivation perspective represents factors that determine a firm's R&D efforts. Past performance, as we will argue, is such a determinant. Building on the capability-based perspective of the firm (Helfat and Winter, 2011; Winter, 2000), the ability to engage in technologies is seen as a function of providing and deploying resources, knowledge and capabilities in a given area (Eggers and Kaul, 2018). As we will argue, board capital provides the firm with specific resources and knowledge (Hillman et al., 2000), and is therefore an important determinant of a firm's ability to develop digital technologies. Hence, while a firm's motivation is a key driver of its behavior, the firm's ability to influence such behavior should also be considered, as it sets the constraints of whether the firm's motivation can be realized or not. We integrate these two theoretical mechanisms in a framework, arguing that both exercise important effects on firm behavior, thus allowing to understand the engagement in emerging digital technologies, such as IoT.

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To proxy these two theoretical mechanisms, we build on the performance, strategic development, and board capital literature streams, construing prior economic performance as a proxy of a firm's motivation, and human and social capital as proxies of its ability to pursue such motivation. Thus, in the following, we study the role of these two thus far overlooked aspects in shaping engagement in emerging digital technologies, and offer complementary explanations to understand this firm behavior by considering a specific type of emerging technology, i.e., IoT solutions.

The motivation to engage in emerging digital technologies, such as IoT

Research argues that a firm's prior economic performance significantly affects its future strategic development, seen as an important motivator for firms to engage in adding new technologies to their resource base (e.g., Eggers and Kaul, 2018). While higher economic performance might provide firms with the necessary financial resources to engage in innovation activities and technological development, it has also been identified as a central indicator explaining learning myopia (Levitt and March, 1988), inertia (Hannan and Freeman, 1984), and rigidities (Leonard-Barton, 1992). Instead, poor economic performance may signal the need to escape from less prosperous operations (Stimpert and Duhaime, 1997) and promote change (Greve, 1998). As such, prior economic performance is found to determine a firm's scope through its impact on diversification (Rumelt, 1974; Stimpert and Duhaime, 1997), acquisition strategy (Park, 2002, 2003), or alliances (Baum et al., 2016), but also on governance (Core et al., 1999) and risk (Audia and Greve, 2006). In the following, we present two theoretical mechanisms explaining how a firm's prior performance level is expected to affect its engagement in emerging digital technologies, such as IoT solutions. We consider, on the one hand, the mechanisms induced by high prior performance, and on the other, discuss the implications of unsatisfactory or low performance.

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Outstanding firm performance is a desirable outcome for both owners and managers (Barkema and Gomez-Mejia, 1998; Hillman and Dalziel, 2003). While managers strive to maximize firm performance to satisfy shareholders and obtain the resources needed for future investments, prior research also argues that performing well in the past might lead to myopia (Levitt and March, 1988). Indeed, falling into a success trap where exploitation is overemphasized and exploration is largely neglected leads to not recognizing necessary changes (Jansen et al., 2006; Levitt and March, 1988; March, 1991; Raisch and Birkinshaw, 2008). This is a general pattern observed in established firms mostly characterized by substantial success, as Christensen (1997) describes in many corporate cases. Often, successful firms fail to respond to radical technological change, such as the

Deleted: , most notably in the hard disk drive and computer industry type needed to develop IoT technologies, as growing inertia reduces their flexibility (Hannan and Freeman, 1984; Kelley and Amburgey, 1991). Inertia fostered by strong organizational identity (Tripsas, 2009) and managers' cognitions (Tripsas and Gavetti, 2000) is linked to a growing set of routines (Nelson and Winter, 1982) that can become barriers to innovation and change, especially toward emerging technologies, such as IoT solutions. Rooted in social theory, routines are seen as a strong feature of bureaucracy potentially leading to stagnation (Feldman and Pentland, 2003). Indeed, well performing firms tend to be satisfied (Winter, 2000), thus believing that their existing routines and knowledge are sufficient, with little incentive to explore novel solutions (Tripsas and Gavetti, 2000). Examples in the innovation literature show that routines are often reflected in a given firm structure, suited to a specific product architecture (Christensen, 1997). However, as changes at the product level occur, these structures might lead established innovators to fail (Christensen, 1997). In a similar vein, capabilities that were once valuable to develop a certain product architecture often produce core rigidities that prohibit successfully adapting to new technological solutions and products (Leonard-Barton, 1992). Based on these arguments, we conclude that performing well in the past hinders firms from adapting their technology base toward emerging IoT technologies.

In addition to considering the impact of high prior performance, we adopt a complementary view on how poor performing firms are driven to develop emerging digital solutions to adapt their technology base. Poor performance is an undesirable outcome for managers and owners (Shaw and Zhang, 2010). When firms face undesirable performance, research indicates that managers might face resource constraints, but at the same time tend toward greater risk-taking (March and Shapira, 1987), seeking organizational change and especially alternative fields of operation (Greve, 1998). Indeed, underperformance may determine the shift in managerial focus from adaptation to survival, in turn leading to threat-rigidity (March and Shapira, 1992; Greve, 2011). In the related

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diversification literature, the "escape hypothesis" (Rumelt, 1974; Stimpert and Duhaime, 1997) proposes that value-maximizing firms choose a diversification strategy based on pre-existing firm characteristics (Campa and Kedia, 2002; Maksimovic and Phillips, 2002) and industry structure (Burch et al., 2000). These studies find that decisions to enter new industries and product markets are driven by poor firm performance (Miller, 2004), which is likely due to the overly competitive, slow growing, and non-innovating industries they are in (Rumelt, 1974; Stimpert and Duhaime, 1997). Hence, poorly performing firms strongly seek alternative industries with better prospects (Stimpert and Duhaime, 1997) and change their market context (Greve, 1998). Without considering the effect of the external industry environment, such firm behavior is also found in the innovation context. As firms enter a stage of organizational decline (Mone et al., 1998), they are stimulated to start corrective processes (Singh, 1986) that increase their innovation activity, especially when considering emerging and resource-absorbing types of innovation, such as IoT. Organizational decline, eventually resulting in organizational crisis, is therefore likely to foster digital innovation (Billings et al., 1980). Given this general change and escape logic in the diversification and innovation literature, we consider underperformance as a driver of developing emerging IoT technological solutions.

Based on these arguments, we contend that firms with superior performance are limited in engaging in emerging technologies, such as IoT solutions, as they tend to rely on established organizational patterns and routines, and hence fail to adapt and renew their technology base to meet digital demands. In addition, we propose that firms with poor performance are driven to adopt IoT technology, as a series of mechanisms leads them to react to their underperformance. Therefore, we hypothesize:

H1: Prior firm economic performance is negatively related to engagement in emerging digital technologies, such as IoT solutions.

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The ability to engage in emerging digital technologies, such as IoT

Although underperforming firms are more willing to extend their technology base and innovation trajectory toward emerging digital technologies, some might be either restricted or enabled by the resources and guidance that their leading personnel provide (Shao et al., 2017). Research has reported that while top management teams (TMTs) are ultimately responsible for strategic decisions, such as engaging in IoT solutions, they are very unlikely to engage in such decisions without board support (Hill and Davies, 2017). The board of directors is argued to have both a monitoring and resource provision function (Hillman and Dalziel, 2003). In this study, we are specifically interested in board capital as the ability to provide specific resources and knowledge to the firm (Hillman et al., 2000). Recent research highlights the crucial role of board directors in "developing the organization's capacity to pivot into uncharted territory" (Hill and Davies, 2017, p.104). This is consistent with resource dependence theory (Pfeffer and Salancik, 1978), which indicates resource provision as a main function of the board of directors (Hillman and Dalziel, 2003), hence suggesting that the board can play an important role in overcoming the firm's resource constraints by providing access to skills, expertise, and networks (Haynes and Hillman, 2010; Huse, 2007; McNulty and Pettigrew, 2016; Westphal and Zajac, 1998). In fact, the extent to which the board can contribute to strategic decision-making processes depends on the directors' ability to bring in knowledge, experiences, competences, and relationships (Minichilli et al., 2009). Such forms of board capital are essential for the board to effectively fulfill its strategic tasks, such as supporting engagement in IoT technologies in response to prior economic performance (Arzubiaga et al., 2018; Huse, 1995). Indeed, resource dependence theory suggests that boards are information-processing structures whose success is based on the knowledge, expertise, and social connections that the directors share with other directors (Dalton and Dalton, 2011). According to this theory, board capital provides resources, such as advice or links to other organizations (Hillman and Dalziel, 2003), and is typically divided into human and social capital (Tian et al., 2011). We argue that both human and social board capital influence the relationship between prior performance and emerging digital solutions, such as IoT technologies.

On the one hand, Becker (1975) and Coleman (1988) define human capital as an individual's expertise, experience, knowledge, and skills. A board's human capital is described as the sum of context-specific expertise, skills, and knowledge obtained through work experience (Hillman and Dalziel, 2003). Often, such expertise specifically relates to the focal firm's operations and established industry environment. Board members with strong industry-specific expertise and experience in the established field are likely to be closely intertwined with current firm operations, processes, routines, and practices (Hillman and Dalziel, 2003; Tian et al., 2011). This deep exposure to firm specific expertise and tacit knowledge can be used to enhance value creation in the firm (Kor, 2003; Rajagopalan and Datfa, 1996; Vancil, 1990), but the focus of these directors is often on improving the organization's capacity to execute its current strategy and sustain core activities (Hill and Davies, 2017). This inhibits directors from engaging in change and exploration activities beyond the firm's current operations (Hill and Davies, 2017; Hillman and Dalziel, 2003; Tian et al., 2011). Hill and Davis (2017) discuss this limiting effect of directors on more discontinuous innovation activities, reporting the example of an automotive company's board of directors that for years discouraged management from making the leap to electric cars. Hence, strong human capital in the form of considerable expertise and experience in the firm's current focal operation and industry environment reduces the firm's ability to engage in IoT technologies and explore new innovation strategies. Thus, we formulate the following hypothesis:

H2a: Board human capital negatively moderates the relationship between prior firm economic performance and engagement in emerging digital technologies, such as IoT solutions.

Social capital, on the other hand, is constituted of resources accessible through an individual's network of relations (Adler and Kwon, 2002; Hillman and Dalziel, 2003; Kwon and Adler, 2014; Tian et al., 2011). Hence, a board's social capital can be defined as the sum of a board's relationships with the firm's external environment. These links may enable directors to provide communication channels outside the organization, but also facilitate the transfer and absorption of resources, such as information on recent trends, market changes, and new knowledge and technologies (Hillman et al., 2000; Hillman and Dalziel, 2003). These multiple relationships increase the diversity of information and knowledge, thereby complementing rather than duplicating the existing knowledge and expertise of top management, which has a positive effect on the firm's ability to engage in more discontinuous innovation activities beyond improving current operations, products, and processes (Hill and Davies, 2017). Therefore, firms that exploit these diverse relationships might be more capable of responding to prior economic performance through sensing the need to innovate by developing emerging technologies, such as IoT solutions. Board social capital hence decreases the hampering effect of prior economic performance on the motivation to engage in developing digital technological resources. Therefore, our last hypothesis is as follows:

H2b: Board social capital positively moderates the relationship between prior firm economic performance and engagement in emerging digital technologies, such as IoT solutions.

Methodology

Sample and data

To test our hypotheses, we relied on a sample of large US manufacturing firms, as the US is deemed the leading global driver of IoT technology development (Ardito et al., 2018). We focus on this US sample between 2002 and 2012. This timeframe is appropriate in the context of our analysis, as it allows capturing the IoT phenomenon right after its advent in 1999 (Ashton, 2009). Given the truncation problem associated with the use of patent data in very recent years, we limited our sample to 2012, as the five most recent years might suffer from missing patents still in the granting process (Hall et al., 2001). In our sample, we included all independent, domestically owned firms that appeared at least once on the Fortune 500 list in terms of sales during our observation period (Arora et al., 2016). We thereby followed a well-established process in creating our US firm-level sample (Qian, 1997; Qian and Li, 2002; Su and Tsang, 2015). To specifically avoid survival and newness bias, our sample includes new entries (either when a firm is newly formed or starts reporting) and exits (bankruptcies or acquisitions) during the observation period, thus resulting in an unbalanced panel[1]. As we build on technology data, capturing a firm's engagement in IoT technologies based on patent data, we excluded firms from the non-manufacturing and services industries, such as those in the financial sector, brokers, insurance, and real estate (due to missing technology patent data), holdings, investment offices, as well as utilities and foreign subsidiaries, as these firms are less likely to protect their innovations with patents (Castellacci, 2008). We focus on manufacturing firms given that these are expected to be mainly driven to adapt their technology base to IoT solutions by moving toward the servitization of business activities (Ardito et al., 2018; Coreynen et al., 2017; EY, 2016).

We collected data by combining multiple data sources. We first relied on the Thomson Innovation database to access firm-level patent data (Stephan et al., 2017). Second, to construct the board level variables, we collected board-level data through the Thomson Reuters ESG Asset4 Database (Bettinazzi and Zollo, 2017). Finally, we drew annual data on firm-level controls from

[1] Therefore, our dataset contains a varying number of firms for each year respectively. This sample compilation does not raise any particular issues regarding estimation and inference (Wooldridge, 2002).

the Worldscope Datastream and Worldscope Segment databases. After excluding firms with missing data on any of our variables, we arrived at a final unbalanced panel of 204 firms with 1,106 firm-year observations.

Variables

Dependent variable - digital IoT technologies

We measured our dependent variable with a firm's *IoT patent share*. As reflected in the widespread reliance on patent-based measures, the literature on firms' technology base sees technology as "a body of knowledge (…) that falls in areas containing in principle patentable knowledge", the operationalization of which "is immensely aided by the international patent system" (Granstrand 1998, p. 466). Therefore, a firm's share of patents related to IoT solutions adequately captures whether a firm engages in IoT technologies by adding this specific knowledge to its technological resource base. We constructed this measure by first counting all annual firm patents for a given priority year. The priority year was chosen over other dates, such as the application or grant date, as it is closest to the time of invention (Ernst, 2001; OECD, 2009; Schmoch, 1988). We then followed Ardito et al. (2018) to define IoT related patents based on International Patent Classification (IPC) codes. A patent is classified as an IoT patent when it falls into one of 10 specific classes. These specific classes are part of one of the four broad technological categories of network system technologies (H04L12/28, H04W84/18, and H04W4/00), communication control technologies (H04L29/08, H04L29/06, and G05B19/418), wireless transmission technologies (G08C17/02, H04B7/26, and H04W72/04), and data processing technologies (G06F15/16). In Table 1, we report the IPC code description. We then calculated the IoT patent share as IoT related patents relative to the total stock of the firm's patents for a given priority year.

Table 1
IPC classes in the IoT domain (Ardito et al., 2018)

IPC Code	Description
G05B019/418	Total factory control, i.e., centrally controlling a plurality of machines, e.g., direct or distributed numerical control (DNC), flexible manufacturing systems (FMS), integrated manufacturing systems (IMS), computer integrated manufacturing (CIM)
G06F015/16	Combinations of two or more digital computers each having at least an arithmetic unit, a program unit and a register, e.g., for simultaneous processing several programs
G08C017/02	Using a radio link
H04B007/26	At least one of which is mobile
H04L012/28	Characterized by path configuration, e.g., LAN [Local Area Networks] or WAN [Wide Area Networks] (wireless communication networks H04W)
H04L029/06	Characterized by a protocol
H04L029/08	Transmission control procedure, e.g., data link-level control procedure
H04W004/00	Services or facilities specially adapted for wireless communication networks
H04W072/04	Wireless resource allocation
H04W084/18	Self-organizing networks, e.g., ad hoc networks or sensor networks

Independent variable – prior firm performance

We measured prior economic firm performance as *Return on Assets* (ROA) – net operating income before extraordinary items divided by total assets – one year prior to our dependent variable (Park, 2002). ROA is the most widely used performance measure in strategic management research, since it allows capturing a firm's profitability relative to its total assets (Keats and Hitt, 1988; Mayer and Whittington, 2003; Palich et al., 2000). Annual data was obtained from the Worldscope database.

Moderator variables – board social capital and board human capital

We captured the two dimension of board capital – board social and board human capital –each with two measures, respectively: *board human capital* is proxied by *CEO experience (HCI)* and *board executive members (HC II); board social capital* is instead captured by the share of *independent board members (SC I)* and the average *external affiliations (SC II)* of board members. Following prior research, we rely on the data provided by the Thomson Reuters ESG Asset4 database to collect this board-level information (Bettinazzi and Zollo, 2017; Cheng et al., 2014;

Claassen and Ricci, 2015; Velte, 2016). *CEO experience* (HC I) is captured by a dummy variable indicating whether for a given year the chair of the board was a prior CEO of the firm (Quigley and Hambrick, 2012). If the board chair was previously CEO, s/he provides strong human board capital as s/he has gathered extensive professional firm and industry specific experience and knowledge as an executive leading the corporation (Hillman and Dalziel, 2003; Tian et al., 2011). *Board executive members* (HC II) is measured by the percentage of board members who also hold an executive role in the firm. Again, this variable is a strong indicator of board members' direct degree of involvement in the firm's prior strategic and operational decisions (Roberts et al., 2005). The measure of a firm's social board capital is *independent board members (SC I)*, reflecting the number of independent members or outside board members relative to the total number of board members (Shivdasani and Yermack, 1999). More independent members or outsiders can be considered connective ties to the firm's external (social) environment, therefore representing strong board social capital (Hillman and Dalziel, 2003; Tian et al., 2011). *Board external affiliations (SC II)* provides a second indicator of a board's social capital, captured by the board members' average number of other corporate affiliations (Hillman et al., 2000).

Control variables

Our model includes several control variables at the board, firm, industry, and macro level. At the board level, we controlled for *board tenure* and *board size.* Board tenure is the average tenure of the total board for a given year, signaling a board's quality, expertise, and experience (Vafeas, 2003). We also controlled for board size (total number of members on the board for a given year), as this is shown to affect firm performance (Eisenberg et al., 1998). At the firm level, we introduced *ownership concentration, firm size, R&D intensity, product diversification*, *technological diversification,* and *IoT distance*. Ownership concentration is captured by the percentage ownership share of the firm's single biggest owner. We controlled for firm size as the firm's total assets, since prior research shows that firm size can cause inertia and affect competitive behavior (Chen and Hambrick, 1995). A firm's R&D intensity, annual R&D expenses divided by total assets, indicates commitment to innovation and research (Griliches, 1981), and is therefore an important control in our study. The firm's level of product diversification is an entropy measure based on sales assigned to 4-digit SIC codes (Hautz et al., 2014). This indicates a firm's distribution across industries and is shown to be associated with innovation (Hitt et al., 1994). We also controlled for technological diversification at the firm level using an entropy measure based on the 3-digit IPC level (Kim et al., 2016). The firm's general level of technology scope indicates its breadth or depth of technological knowledge determining innovation (Leten et al., 2007). Finally, we included industry- and macro-level controls in our model. Specifically, we measured industry growth in a firm's 2-digit SIC core industry as the annual value added at current prices, indicating the attractiveness of a chosen industry (Bowen and Wiersema, 2005). At the macro level, we account for the macro environment effect on innovation activities by capturing the annual growth of the US economy from the WDI database (Lundvall, 2007). Further, we use a dummy to control for the effects of the global financial crisis in 2008, since the period before the crisis is potentially characterized by different innovation and financing patterns than subsequent years (Campello et al., 2010).

Model specification and analysis

To test our hypothesized relationships, we used panel regression analysis with interaction terms. Prior research has indicated endogeneity issues between performance and other firm-level variables (Iyengar and Zampelli, 2009; Miller, 2006). To test for such potential endogeneity between prior performance and engagement in digital technologies, such as IoT solutions, we estimated a two-stage-least-squares (2SLS) instrumental variable regression. We captured the firm's level of international exposure through its foreign sales ratio (Chen and Tan, 2012; Tan and Mathews, 2015), and included the second lag of the foreign sales ratio as well as the squared value of its second lag as instrumental variables. Including these instruments in our 2SLS regression satisfies the conditions for over- and under-identification and instrument validity (Baum et al., 2003, 2007; Cragg and Donald, 1993; Kleibergen and Paap, 2006; Sargan, 1988; Stock et al., 2002) at the 5% significance level. We subsequently tested for the endogeneity of prior performance and could not reject the null hypothesis of exogeneity, which signals no endogeneity of prior performance in our equation. Following this result, we proceeded with OLS regression. We further applied a Hausman test to compare the fixed- and random-effects models (Hausman, 1978), and found significant differences in the estimates, hence rejecting a random effect specification. Therefore, we chose the fixed effects specification, which additionally allowed us to account for unobserved firm-specific characteristics (Greene, 2012; Sugheir et al., 2012). Our basic model describes the relationship between IoT patent share and prior performance as follows:

$$\textbf{IoT patent share}_{it} = \beta_0 + \beta_1 \textbf{ prior performance}_{it-1} + \beta_2 \textbf{ controls}_{it-1} + \beta_3 \textbf{ year}_t + u_i + \varepsilon_i$$

Our second model includes interaction terms between prior performance and board capital, both in terms of human and social capital. The following specification applies:

$$\textbf{IoT patent shareit} = \boldsymbol{\beta}\textbf{0} + \boldsymbol{\beta}\textbf{1 prior performanceit-1} + \boldsymbol{\beta}\textbf{2 prior performanceit-1 x board capitalit- 1} + \beta_3 \textbf{ controls}_{it-1} + \beta_4 \textbf{ year}_t + u_i + \varepsilon_i$$

In these equations, we also control for time effects by including year dummies. All our independent variables are lagged by one year (Kim et al., 2016). In our models, *ui* includes the firm specific characteristics and *εi* is the idiosyncratic error term.

Results

Table 2 shows the descriptive statistics and the correlation matrix of our sample. We mean-centered our independent variables, moderators, and their interaction terms to avoid any bias due to multicollinearity. Table 3 reports the results of our regression analysis. In Model 1, we show our baseline model with controls. The coefficient estimates for the control variables are by and large as expected. In Models 2–5, we first respectively and then jointly added prior performance and our board variables, representing human and social board capital. We find support for our first hypothesis (H1) predicting the negative effect of prior performance on IoT related patents across all our models, thus suggesting that an increase in performance by 1% decreases the share of IoT related patents in the subsequent year by 0.036% (Model 4).

In Models 6–8 we tested our hypotheses H2a and H2b concerning the impact of board social and human capital on this relationship. We added interaction terms between prior performance and the board human capital and board social capital variables, separately and jointly. The R^2 and F-statistics show that the model fit increases when considering the moderation variables. We consistently find a significant negative interaction term between prior performance and both our board human capital variables, CEO experience (HC I) ($p<0.01$) and board executive members (HC II) ($p<0.01$) (see Models 6 and 8), hence providing support for H2a. With increasing levels of human board capital, the negative effect of prior performance on IoT patents is reinforced. H2b, in contrast, is only partially supported by our results. Model 7 reports a positive significant interaction effect ($p<0.01$) of one board social capital variable, board independent members (SC I).

Table 2
Descriptive statistic and correlation matrix.

Variables	Mean	Std. Dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) IoT patent share	3.9924	9.2260	1.0000														
(2) Prior performance ROA	5.4403	8.7669	-0.0793*	1.0000													
(3) B independent members (SC I)	29.3996	13.3832	-0.0805*	0.0677*	1.0000												
(4) B external affiliations (SC II)	0.1488	0.7956	-0.0272	-0.0205	-0.0362	1.0000											
(5) B CEO experience (HC I)	0.5289	0.4994	-0.0856*	0.0349	0.0369	-0.0401	1.0000										
(6) B executive members (HC II)	-23.1973	6.4798	0.1519*	-0.0921*	-0.5042*	-0.0296	-0.0388	1.0000									
(7) B tenure	8.4766	2.8206	-0.0671*	0.0832*	-0.0881*	-0.1344*	0.0845*	0.1355*	1.0000								
(8) B size	10.7839	1.9148	-0.0650*	0.0333	0.1542*	0.0682*	0.1036*	-0.1618*	-0.0121	1.0000							
(9) Ownership concentration	11.6195	9.9264	-0.0073	-0.0892*	-0.2442*	-0.0183	-0.1069*	0.1533*	-0.1074*	-0.1130*	1.0000						
(10) Firm size	16.0230	1.1336	0.2310*	0.0539	0.1220*	0.1614*	0.0683*	-0.0899*	-0.1191*	0.3836*	-0.0776*	1.0000					
(11) R&D intensity	5.6258	6.9335	0.2626*	-0.1297*	-0.1444*	-0.0373	-0.0331	0.1780*	0.0286	-0.1212*	-0.0650*	0.0062	1.0000				
(12) Technological diversification	1.9501	0.7433	-0.2963*	-0.0256	0.1136*	0.1443*	0.0652*	-0.1149*	0.045	0.1134*	-0.0738*	0.1759*	-0.2044*	1.0000			
(13) Product diversification	0.3248	0.3939	-0.057	-0.0327	0.0856*	0.1389*	0.0368	-0.1231*	0.1071*	0.0803*	-0.1020*	0.1992*	-0.2519*	0.3440*	1.0000		
(14) Industry growth	-0.1328	3.9347	0.0053	0.0841*	-0.1094*	0.1617*	-0.0672*	0.0919*	-0.0474	-0.0431	0.0432	-0.0257	0.0179	0.0474	0.0224	1.0000	
(15) GDP growth	1.1740	2.2700	-0.0006	0.018	-0.0467	0.2367*	-0.0293	0.1203*	-0.0649*	-0.0689*	0.0532	-0.0766*	0.0471	-0.0039	0.0443	-0.0149	1.0000
(16) Post financial crisis	0.5732	0.4948	0.0091	0.0454	0.2032*	-0.3418*	0.0903*	-0.1575*	0.0823*	0.0965*	-0.0594*	0.1273*	-0.0639*	-0.0683*	-0.0505	-0.4607*	-0.5500*

Observations: 1,106

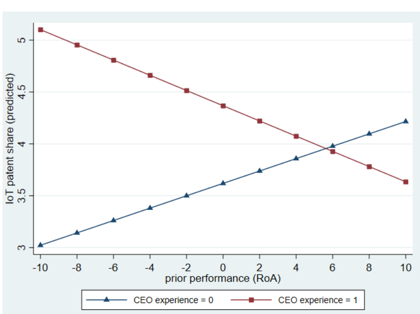
Table 3
Regression analysis: impact of prior firm performance on IoT patent share and the moderating effects of human and social board capital.

Variables	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*	*Model 8*
Board tenure	-0.011	-0.005	-0.007	-0.009	-0.008	-0.028	-0.001	-0.022
	(-0.12)	(-0.05)	(-0.08)	(-0.10)	(-0.09)	(-0.32)	(-0.01)	(-0.24)
Board size	0.158	0.158	0.161	0.160	0.162	0.220*	0.190	0.220*
	(1.26)	(1.27)	(1.29)	(1.27)	(1.29)	(1.81)	(1.54)	(1.81)
Ownership concentration	-0.052**	-0.054**	-0.058***	-0.055***	-0.058***	-0.059***	-0.064***	-0.058***
	(-2.49)	(-2.57)	(-2.72)	(-2.59)	(-2.70)	(-2.83)	(-3.03)	(-2.79)
Firm size (log)	-0.585	-0.566	-0.534	-0.576	-0.541	-0.420	-0.581	-0.513
	(-1.14)	(-1.10)	(-1.04)	(-1.12)	(-1.04)	(-0.83)	(-1.13)	(-1.01)
R&D intensity	0.065	0.018	0.016	0.013	0.013	-0.232***	-0.213***	-0.235***
	(1.15)	(0.30)	(0.25)	(0.20)	(0.21)	(-3.13)	(-2.85)	(-3.11)
Technological diversification	-1.002**	-1.019**	-1.005**	-1.003**	-0.999**	-0.930**	-0.924*	-0.916**
	(-2.08)	(-2.12)	(-2.09)	(-2.08)	(-2.07)	(-2.00)	(-1.94)	(-1.97)
Product diversification	1.661	1.516	1.518	1.588	1.551	1.446	1.328	1.347
	(1.37)	(1.25)	(1.25)	(1.30)	(1.27)	(1.23)	(1.11)	(1.14)
Industry growth	-0.009	0.003	0.001	-0.001	-0.000	-0.034	-0.029	-0.040
	(-0.15)	(0.04)	(0.02)	(-0.01)	(-0.00)	(-0.57)	(-0.48)	(-0.67)
GDP growth	-0.057	-0.047	-0.049	-0.056	-0.053	-0.083	-0.075	-0.086
	(-0.47)	(-0.39)	(-0.41)	(-0.46)	(-0.44)	(-0.70)	(-0.62)	(-0.73)
Post financial crisis	0.145	0.165	0.177	0.157	0.174	-0.119	-0.014	-0.152
	(0.19)	(0.22)	(0.23)	(0.20)	(0.23)	(-0.16)	(-0.02)	(-0.20)
Prior performance ROA		-0.036*	-0.036**	-0.035*	-0.036*	-0.143***	-0.211***	-0.163***
		(-1.94)	(-1.98)	(-1.90)	(-1.95)	(-4.40)	(-5.82)	(-4.31)
Board independent members (SC I)			-0.014		-0.013	-0.019	-0.045***	-0.027*
			(-1.24)		(-1.07)	(-1.61)	(-3.32)	(-1.90)
Board external affiliations (SC II)			0.028		0.031	0.035	0.133	0.127
			(0.13)		(0.15)	(0.17)	(0.60)	(0.58)
Board CEO experience (HC I)				-0.047	-0.029	0.726*	0.062	0.749*
				(-0.12)	(-0.08)	(1.76)	(0.16)	(1.81)
Board executive members (HC II)				0.019	0.009	0.026	-0.009	0.022
				(0.67)	(0.30)	(0.91)	(-0.30)	(0.78)
Prior performance ROA x Board CEO experience (HC I)						-0.133***		-0.133***
						(-4.28)		(-4.28)
Prior performance ROA x Board executive members (HC II)						-0.009***		-0.008***
						(-7.31)		(-4.33)
Prior performance ROA x Board independent members (SC I)							0.006***	0.002
							(5.49)	(0.92)
Prior performance ROA x Board external affiliations (SC II)							-0.014	-0.020
							(-0.75)	(-1.09)
Constant	13.323	13.518*	13.465*	14.146*	13.763*	12.869	15.753*	14.424*
	(1.64)	(1.67)	(1.66)	(1.72)	(1.67)	(1.61)	(1.93)	(1.79)
Observations	1106	1106	1106	1106	1106	1106	1106	1106
R^2	0.032	0.037	0.038	0.037	0.038	0.106	0.071	0.108

Notes: *t* statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01, time dummies excluded, interaction terms mean-centered, one year lag between the dependent and independent variables.

This positive effect is not reported in Model 8, which includes all four interaction terms. Our second variable for social capital, board external affiliations (SC II), remains insignificant in both models.

The nature of these significant interactions between prior performance and human board capital and prior performance and social board capital is further illustrated in Figs. 1 and 2. Figs. 1a and 1b represent the relationship between prior firm performance and IoT patent share at different levels of the two dimensions of human board capital. Fig. 1a illustrates the relationship of whether the CEO has prior experience in the firm or not (HC I). Fig. 1b shows the impact of prior performance on IoT patents at different levels of board members who are also executives of the firm (HC II), including the mean level and one standard deviation above and below the mean level of this variable. The interaction plot in Fig. 1a shows the negative effect of prior firm performance on IoT technology share if the chair of the board was previously the firm's CEO. Vice versa, a positive effect of prior performance on IoT patent share occurs if the chair of the board was not previously CEO.



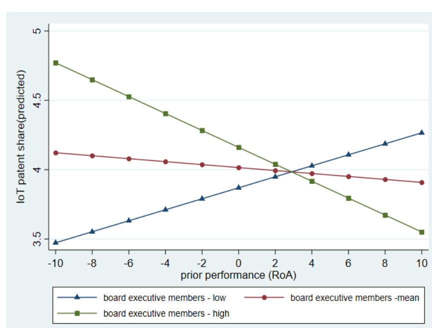


Fig. 1a: Moderating effect of human board capital (HC I, CEO experience) on the relationship between prior firm performance and IoT share.

Fig. 1b: Moderating effect of human board capital (HC II, board executive members) on the relationship between prior firm performance and IoT share.

Fig. 1b also confirms the negative moderation of a large share of board members (HC II) who also hold an executive role in the firm. While at mean levels, the relationship between prior performance and IoT technology share is still slightly negative, this negative relationship is reinforced with an increasing share of firm executives also serving on the board. In contrast, if there are only few executive members on the board, the relationship becomes positive.

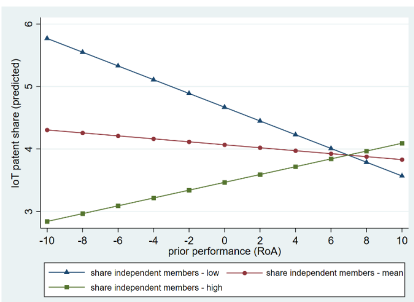


Fig. 2a: Moderating effect of human board capital (SC I, independent board members) on the relationship between prior firm performance and IoT share (Model 6).

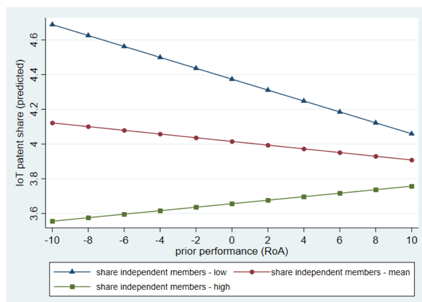


Fig. 2b: Moderating effect of human board capital (SC I independent board members) on the relationship between prior firm performance and IoT share (Model 8).

Fig. 2 consider the moderating effect of board social capital, showing the relationship between prior firm performance and IoT technologies at different levels of independent board member shares (SC I), including the mean level and one standard deviation above and below the mean level of this variable. Both figures illustrate the positive moderation effect of this dimension of social board capital. While the impact of prior performance on IoT share is negative at low and mean levels of independent board members, the relationship becomes positive with an increasing share of independent board members. However, Fig. 2b also reveals that this positive effect of board social capital becomes less pronounced when jointly considered with the moderation effect of board human capital, as in Model 8.

Robustness tests

To provide robustness for our results, we performed several additional tests (the results are available upon request). First, we re-estimated our models as random effect models, which confirmed the results derived from the fixed effects estimation.

As a second robustness check, we applied return on investment (ROI) as an alternative measure of performance. The results remain unchanged and robust against the selection of our performance variable. In addition, following Gilsing et al. (2008), we captured the extent to which IoT technologies are more or less distant from a firm's existing technological base as additional control variable. Specifically, for each IoT patent in a 4-digit IPC, we checked whether the firm already had another patent in this respective subordinate 4-digit IPC class in the previous five years. Accordingly, if the firm had successfully applied for a patent in the previous five years in the respective 4-digit IPC class, we coded the particular IoT patent as close (exploitative) to the firm's technological base, otherwise as distant (explorative). We then summed up explorative and exploitative IoT patents and calculated a continuous measure (∑ explorative IoT patents /(∑explorative IoT patents + ∑exploitative IoT patents) ranging from zero to one, where a higher score indicates that a firm's existing knowledge base is more distant from the IoT domain. Again, our results remain unchanged when adding this additional control variable.

Next, as our data showed some proportion of zeros in our dependent variable IoT patent share, we ran an additional sub-sample analysis in which we excluded all firms reporting no IoT related patents in a given sample year. Again, our results remain unchanged. We also combined robustness checks by controlling for IoT distance in this reduced sample, and again our findings are stable.

In addition, we combined our two measures for each dimension of board capital to obtain a single measure for human board capital and a single measure for social board capital. We therefore reduced the information of our three continuous board capital variables (board executive members, board independent members, and board external affiliations), and transformed them into dummy variables. This transformation was based on the sample mean of these variables, resulting in a dummy of one if an observation on a respective variable was above the sample mean, and zero if the observation was below the sample mean. We then combined the dummies for CEO experience and board executive members into one joint dummy representing human board capital, and board independent members and board external affiliations into one joint dummy representing social board capital The joint dummy was classified as 1 if one of the two dimensions was characterized as 1, 0 otherwise. We reran our entire analysis including the two dummy variables for human and social board capital as moderators. Our results are supported with the combined measures, showing a significant negative effect of prior performance, a significant negative interaction effect with the board human capital dummy, and a significant positive effect with the board social capital dummy.

Supplemental analysis

Based on our interaction analysis and results, we have some reason to expect that the board human capital dimensions and the board social capital dimensions affect and interact in the relationship between firm prior performance and engagement in IoT related technologies. To obtain a more detailed and nuanced understanding of this joint effect, we conducted supplemental analyses and added three-way interactions between prior performance, the board human capital variables, and board social capital variables to our models (see Table 4, Models 9–12). Indeed, we find significant three-way interactions. Model 9 reports a positive significant ($p<0.01$) interaction term between prior performance, board CEO experience (HC I), and the share of independent board members (SC I). Moreover, we find significant negative interactions between prior performance, board executive members (HC II), and independent board members (SC I) ($p< 0.01$, model 10), as well as between prior performance, board executive members (HC II), and the extent of external board affiliations (SC II) ($p< 0.01$, Model 12).

Table 4:
Regression analysis: joint impact of prior firm performance, human and social board capital on IoT patent share.

	Model 9	Model 10	Model 11	Model 12
Board tenure	-0.025	-0.013	-0.023	-0.032
	(-0.29)	(-0.14)	(-0.26)	(-0.37)
Board size	0.191	0.224*	0.226*	0.228*
	(1.58)	(1.85)	(1.85)	(1.88)
Ownership concentration	-0.056***	-0.060***	-0.058***	-0.056***
	(-2.72)	(-2.93)	(-2.78)	(-2.71)
Firm size (log)	-0.670	-0.630	-0.545	-0.612
	(-1.32)	(-1.24)	(-1.07)	(-1.21)
R&D intensity	-0.170**	-0.165**	-0.226***	-0.172**
	(-2.20)	(-2.12)	(-2.97)	(-2.21)
Technological diversification	-0.925**	-0.893*	-0.888*	-0.942**
	(-1.99)	(-1.93)	(-1.90)	(-2.03)
Product diversification	1.321	1.309	1.385	1.454
	(1.13)	(1.12)	(1.17)	(1.24)
Industry growth	-0.034	-0.040	-0.038	-0.043
	(-0.58)	(-0.68)	(-0.65)	(-0.72)
GDP growth	-0.089	-0.094	-0.082	-0.103
	(-0.76)	(-0.80)	(-0.70)	(-0.88)
Post financial crisis	-0.118	-0.207	-0.131	-0.177
	(-0.16)	(-0.28)	(-0.18)	(-0.24)
Prior performance ROA	-0.099**	-0.186***	-0.166***	-0.211***
	(-2.33)	(-4.79)	(-4.36)	(-4.97)
Board independent members (SC I)	-0.003	-0.018	-0.027*	-0.025*
	(-0.17)	(-0.73)	(-1.93)	(-1.77)
Board external affiliations (SC II)	0.109	0.057	0.199	-0.503
	(0.50)	(0.26)	(0.68)	(-0.87)
Board CEO experience (HC I)	2.374***	0.716*	0.820*	0.777*
	(3.12)	(1.74)	(1.88)	(1.89)
Board executive members (HC II)	0.035	0.036	0.024	0.056*
	(1.19)	(1.18)	(0.84)	(1.82)
Prior performance ROA x Board CEO experience (HC I)	-0.366***	-0.112***	-0.140***	-0.131***
	(-4.79)	(-3.55)	(-4.38)	(-4.21)
Prior performance ROA x Board executive members (HC II)	-0.010***	-0.008***	-0.008***	-0.010***
	(-5.19)	(-4.50)	(-4.42)	(-5.03)
Prior performance ROA x Board independent members (SC I)		-0.004*	0.002	0.001
	(-1.16)	(-1.83)	(0.95)	(0.77)
Prior performance ROA x Board external affiliations (SC II)	-0.017	-0.010	-0.038	-0.109***
	(-0.96)	(-0.55)	(-1.45)	(-3.29)
Board CEO experience (HC I) x Board independent members (SC I)	-0.058**			
	(-2.52)			
Board executive members (HC II) x Board independent members (SC I)		0.000		
		(0.36)		
Board CEO experience (HC I) x Board external affiliations (SC II)			-0.122	
			(-0.33)	
Board executive members (HC II) x Board external affiliations (SC II)				-0.024
				(-0.99)
Prior performance ROA x Board CEO experience (HC I) x Board independent members (SC I)	0.008***			
	(3.35)			
x Prior performance ROA x Board executive members (HC II) x Board independent members (SC I)		-0.000***		
		(-3.62)		
Prior performance ROA x Board CEO experience (HC I) x Board external affiliations (SC II)			0.034	
			(0.96)	
Prior performance ROA x Board executive members (HC II) x Board external affiliations (SC II)				-0.004***
				(-3.10)
Constant	16.534**	16.128**	14.774*	16.397**
	(2.05)	(2.01)	(1.83)	(2.04)
Observations	1106	1106	1106	1106
R^2	0.120	0.122	0.109	0.119

Notes: *t* statistics in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$, time dummies excluded, interaction terms mean-centered, one year lag between the dependent and independent variables.

However, three-way interactions are difficult and not straight forward to interpret. Simply finding a significant three-way interaction term is not enough to interpret this effect, but requires additional graphical or even subsample analyses to disentangle the complex question of whether and how the moderation effect of board human capital on the relationship between prior performance and IoT share is dependent on levels of board social capital, or vice versa. To obtain deeper and more detailed insights, we generated interaction graphs for the three significant three-way interaction terms (see Figs. 3a–3c). These figures show a positive relationship between prior firm performance and IoT share when board human capital is low and board social capital is instead high. However, this positive relationship is weakened (Fig. 3a) or even turns negative (Figs. 3b and 3c) if high board social capital is combined with high board human capital.

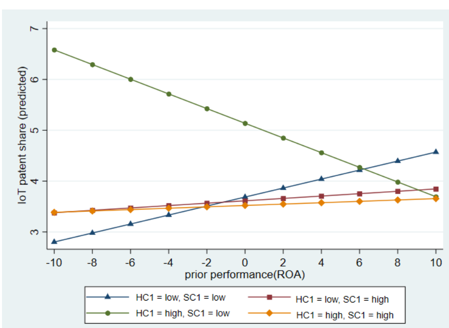


Fig. 3a: Moderating effect of board human capital (CEO experience, HC I) on the relationship between prior firm performance and IoT share dependent on board social capital (board independent members, SC I) (Model 9)

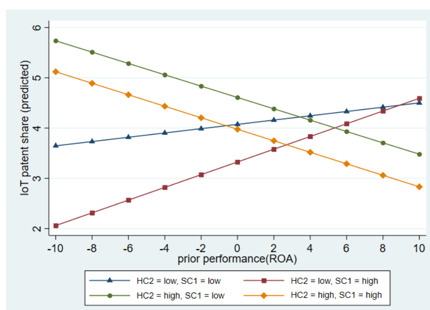


Fig. 3b: Moderating effect of board human capital (board executive members, HC II) on the relationship between prior firm performance and IoT share dependent on board social capital (board independent members, SC I) (Model 10)

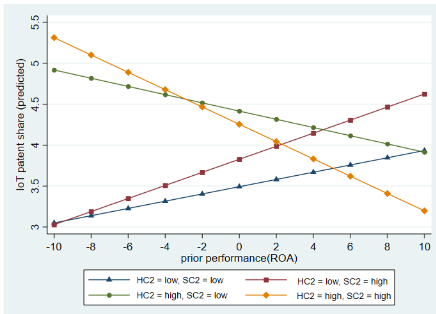


Fig. 3c: Moderating effect of board human capital (board executive members, HC II) on the relationship between prior firm performance and IoT share dependent on board social capital (board external affiliations, SC II) (Model 12)

In contrast, a negative effect of prior performance on the development of IoT patents emerges in all three figures if board human capital is high and board social capital is low. This negative relationship turns positive if combined with high board social capital represented by board independent members (SC I) (Figs. 3a and 3b). However, the board social capital dimension, external board affiliations (SCII), does not have such a positive effect (Fig. 3c).

To further extend our understanding of these interrelationships, we conducted a comparative subsample analysis (Cassiman and Veugelers, 2006; Mayer et al., 2015; Miller et al., 2013). While the interaction term analysis shows that contextual factors, such as board human and social capital, shape the relationship between performance and IoT technology share, this approach directly examines the effect of performance under specific contextual conditions (Klingebiel and Rammer, 2014; Miller et al., 2013). For the three significant interaction terms (Models 9, 10, and 12), we formed subsamples representing combinations of different levels of board social and human capital. For the variables board executive members (HC II), board independent members (SC I), and board external affiliation (SC II), all firms characterized by levels below the sample mean were classified as “low”, while those above the sample mean as “high”. In cases where CEO experience (HC I) is classified as 1, firms were categorized as having high board human capital, and in those classified as 0, low board human capital.

Our sub-sample analysis (Table 5) supports our findings from the graphical analysis. We find a negative effect of prior performance on IoT share in all models whenever board human capital is high and board social capital is low. A positive relationship is found when board human capital is low and board social capital in terms of independent members (SC I) is high. High levels of this dimension of board social capital also turn the negative relationship positive, although not significantly. The case again differs for the social capital dimension of external affiliations (SC II), as in our two-way interaction analysis (shown in the graphical analysis), this dimension of board social capital does not result in a positive moderation effect, and is unable to dampen the negative effect of board human capital.

Table 5
Subsample analysis.

	HCI low SCI high	*HCI high SCI low*	*HCI high SCI high*	*HCII low SCI high*	*HCII high SCI low*	*HCII high SCI high*	*HCII low SCII high*	*HCII high SCII low*	*HCII high SCII high*
Board tenure	-0.073	0.131	-0.006	-0.100	0.117	-0.167	-0.156	0.058	0.176
	(-0.28)	(0.44)	(-0.04)	(-0.54)	(0.52)	(-0.44)	(-1.04)	(0.24)	(0.43)
Board size	0.163	-0.472	0.114	-0.094	0.698**	0.046	-0.002	0.244	0.447
	(0.45)	(-1.19)	(0.76)	(-0.40)	(2.01)	(0.07)	(-0.01)	(0.63)	(0.92)
Ownership concentration	-0.092	0.085	-0.024	-0.077	0.003	0.019	-0.016	-0.198**	0.031
	(-0.73)	(0.96)	(-0.50)	(-1.17)	(0.05)	(0.13)	(-0.38)	(-2.38)	(0.17)
Firm size (log)	-3.939**	-1.171	1.160	-2.740**	1.494	4.395*	0.685	-2.890*	9.338***
	(-2.04)	(-0.69)	(1.49)	(-2.34)	(1.09)	(1.74)	(0.92)	(-1.97)	(3.49)
R&D intensity	-0.389	-0.949***	0.058	-0.062	-0.264**	0.447	0.050	-0.021	-0.583
	(-1.13)	(-2.70)	(0.52)	(-0.37)	(-2.42)	(0.76)	(0.38)	(-0.17)	(-1.59)
Technological diversification	-1.845	0.159	-1.282**	-1.980**	-0.543	-2.279	-0.607	0.765	-3.629**
	(-1.61)	(0.13)	(-1.99)	(-2.51)	(-0.47)	(-1.54)	(-1.03)	(0.64)	(-2.27)
Product diversification	1.008	2.806	1.551	1.367	1.442	-3.968	1.837	3.460	-6.277
	(0.23)	(0.75)	(1.08)	(0.69)	(0.45)	(-0.62)	(1.39)	(0.92)	(-1.23)
Industry growth	-0.050	-0.052	-0.014	-0.054	-0.007	-0.122	0.036	0.013	-0.192
	(-0.32)	(-0.29)	(-0.23)	(-0.60)	(-0.04)	(-0.71)	(0.44)	(0.09)	(-0.64)
GDP growth	-0.186	-0.096	-0.094	-0.245	-0.107	-0.132	0.009	-0.165	-0.261
	(-0.59)	(-0.25)	(-0.77)	(-1.33)	(-0.28)	(-0.38)	(0.05)	(-0.53)	(-0.46)
Post financial crisis	1.633	-0.969	-0.640	-0.281	0.333	-1.762	0.175	1.223	-3.533
	(0.83)	(-0.46)	(-0.81)	(-0.24)	(0.15)	(-0.84)	(0.18)	(0.61)	(-1.17)
Prior performance ROA	**0.101****	**-0.418*****	**0.010**	**0.064****	**-0.238*****	**0.003**	**-0.040****	**-0.106***	**-0.174*****
	(2.17)	**(-6.71)**	**(0.40)**	**(2.22)**	**(-5.30)**	**(0.06)**	**(-2.01)**	**(-1.90)**	**(-3.22)**
Board independent members (SC I)	0.269**	-0.009	0.037	0.185**	-0.017	-0.070	-0.054***	-0.064	0.042
	(2.34)	(-0.19)	(0.53)	(2.42)	(-0.39)	(-0.39)	(-4.08)	(-1.48)	(0.84)
Board external affiliations (SC II)	0.456	0.336	-0.182	0.183	-0.950	-0.236	0.372	-0.665	-1.238
	(0.83)	(0.42)	(-0.75)	(0.51)	(-1.27)	(-0.48)	(1.29)	(-0.49)	(-1.53)
Board CEO experience (HC I)				0.042	0.906	-0.358	-0.203	-0.614	3.059*
				(0.06)	(0.74)	(-0.23)	(-0.43)	(-0.44)	(1.85)
Board executive members (HC II)	0.122	0.113	0.018	-0.018	0.116	-0.480	-0.027	0.068	0.140
	(0.88)	(1.28)	(0.26)	(-0.09)	(1.44)	(-1.49)	(-0.19)	(0.64)	(1.19)
Constant	63.949**	35.975	-15.973	45.928**	-21.121	-69.123*	-4.821	51.933**	-139.661***
	(2.12)	(1.33)	(-1.25)	(2.46)	(-0.95)	(-1.78)	(-0.40)	(2.17)	(-3.14)
Observations	343	205	380	558	243	165	314	236	172
R^2	0.124	0.443	0.065	0.081	0.345	0.175	0.187	0.213	0.388

Notes: t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01, time dummies excluded, interaction terms mean-centered, one year lag between dependent and independent variables

Discussion and Conclusion

Given the importance of understanding heterogeneity in firm behavior when engaging in emerging technologies, we identify prior economic performance as a proxy of a firm's motivation, and a firm's human and social board capital as proxies of its ability to pursue such motivation. Our analysis of a 10-year US panel dataset shows that underperforming firms are more willing to engage in the emerging IoT domain (Dutta et al., 2014; Shin, 2017), while superior prior firm performance make firms less inclined to engage in these digital technologies. Moreover, given the resource provision function of board members, board human capital reinforces the hampering effect of prior firm performance on engagement in emergent digital technologies, whereas social capital dampens this negative effects. In the following, we discuss the implications of our results for theory and practice, and conclude with the limitations and some future research recommendations.

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Implications for theory

Previous literature has found that established firms vary in the adoption of emerging technologies (Ahuja and Lampert, 2001), looking at the typical pitfalls caused by the specific characteristics of such technologies (e.g., Day and Schoemaker, 2000), their organizational challenges (Khanagha et al., 2013), or the role of managerial attention in exploring emerging fields (Khanagha et al., 2017). While it is evident that firms differ in their exploration of emerging fields, the questions of why some firms are more willing to engage in such endeavor, and what causes differences in technology adoption have not been fully addressed (Khanagha et al., 2017). By adopting the motivation and ability perspective, we integrate two theoretical mechanisms that are important to understand firm behavior and its heterogeneity when considering engagement in emerging digital technologies. Indeed, integrating these perspectives in a framework allows

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reconciling the divergent views by highlighting the contradictions between the dominant coalition's motivation and its ability in relation to digitalization. In particular, we demonstrate that these contradictory dimensions produce motivation and ability effects that explain firms' heterogeneity and variability in engaging in emerging digital technologies.

Prior research emphasizes the importance of the firm's resource and technology base (Barney, 1991; Dosi et al., 2017; Granstrand, 1998; Kim et al., 2016; Pavitt, 1998). In the context of this study, we specifically view a firm's engagement in the IoT domain as the adaption of its technology base to prepare for a change in product architecture alongside digitalization (Ambrosini et al., 2009; Cenamor et al., 2017; Nambisan, 2017). Accordingly, we show that engagement in emerging digital technologies, such as IoT solutions, and the associated reshaping of the technology base are influenced by the dominant coalition's willingness to engage in firm behavior and its ability to deploy of the resources needed to pursue such willingness.

Drawing on the literature on the consequences of prior performance (Park, 2002, 2003), we confirm that especially underperforming firms are more willing and driven to adapt their resource base (Eggers and Kaul, 2018) through IoT technology. Our results suggest that two complementary theoretical perspectives account for this. First, well performing firms are likely to be hindered in renewing their technology base with cutting-edge knowledge in the face of myopia (Levitt and March, 1988), inertia (Hannan and Freeman, 1984), or rigidities (Leonard-Barton, 1992). ~~These mechanisms prevent firms from developing emerging digital technologies, as they fall into a success trap where they discard exploratory learning (Levitt and March, 1988; March, 1991; Raisch and Birkinshaw, 2008), and instead exploit their previous paths of success (Patel and Pavitt, 1997; Sydow et al., 2009).~~ Second, underperformers have to escape from less prosperous operations (Stimpert and Duhaime, 1997), and thus change (Greve, 1998) to overcome their performance deficit. Our results confirm arguments borrowed from the "escape hypothesis" in the diversification

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literature (Stimpert and Duhaime, 1997), suggesting that firms tend to pursue change and resource renewal by developing IoT technologies when confronted with lower performance.

Research following resource dependence theory (Pfeffer and Salancik, 1978) argues that board members provide valuable resources to the focal firm (Hillman et al., 2000; Tian et al., 2011). Although both the board's human and social capital are considered as valuable to the firm (Hillman and Dalziel, 2003), our study suggests that when reorientation is needed, only social capital is favorable. Indeed, being overly expert and experienced in a given industry as a board member (human capital) even strengthens the negative consequences of prior performance on the renewal and reorientation of the technology base. However, board social capital, bringing valuable external links to the firm, increases the ability to explore more distant technology fields (Eggers and Kaul, 2018), and thus develop emerging technologies, such as IoT solutions. Our findings thereby significantly extend the current literature by showing that board capital is not universally beneficial to firms, but rather that the role of board resources in sustaining engagement in new technological domains is performance dependent. Moreover, our study underscores the importance of board resources for business digitalization (Shao et al., 2017), showing that their effects are more complex than previously thought, and can add much to our understanding of firms' heterogeneity in engagement with digital technologies. ~~In addition, our research reveals that resource dependence theory can provide a valuable basis for explaining such complexity (Pfeffer and Salancik, 1978), and that board social capital is a crucial resource for firms to develop emerging digital technologies in response to prior economic performance. Relatedly, we reveal that the resource dependence perspective provides a basis for more precise predictions on the impact of boards on engagement in emergent digital technologies, thus informing future research at the intersection of corporate governance and innovation (O'Connor and Rafferty, 2012; Phan et al., 2009; Tylecote and Ramirez, 2006).~~

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Overall, our analysis responds to repeated calls in the management literature for a greater understanding of the diversity of the digital transformation behavior of firms (Cennamo, 2019). Our theory and evidence advance an integrated view of digitalization as the dominant coalition's motivation to engage in firm behavior, and its ability to deploy the resources needed to pursue such motivation. Hence, our study points to the importance of considering both motivation and ability when examining firm behavior, particularly in the case of emerging digital technologies characterized by specific motivation and ability barriers (Iansiti and Lakhani, 2014; Nambisan, 2017). Indeed, we encourage scholars to take into account variations in the willingness and ability dimensions in future research designs (De Massis et al., 2014).

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Implications for practice

Having shown the theoretical implications of our findings, practitioners can draw important conclusions from our study. First, we suggest managers be aware of the importance of actively considering the renewal and diversification of their technology base in the context of emerging digital technologies. In particular, considering IoT solutions as an important component of developing cutting-edge, smart, intelligent, and interconnected products is inevitable to meet current and future customer needs. Second, while a desirable result, managers need to be aware that performing well today may cause future problems, such as limited technological engagement in emerging digital solutions. Therefore, managers need to actively combat myopia, inertia, or rigidities that ensue from an established product and business logic to ensure the exploration of cutting-edge solutions for future product development. Finally, our study also has strong implications concerning the selection of board members. Firms have to select board members that support the firm in finding the right technology paths to overcome performance difficulties. Especially in times of poor performance, we suggest building on social capital, including external board members from distant industries with different technological competencies. In fact, these members may provide firms with the relationships and resources needed to foster their ability to enter newly emerging cutting-edge technological domains, as in the case of IoT solutions.

Limitations and future research

Despite the contributions of this study, we also acknowledge its limitations that may offer opportunities for future research. As indicated earlier, this is one of the few empirical studies aiming to disentangle the two theoretical mechanisms of motivation and ability in the context of emerging technologies, and especially IoT solutions, at the firm level through a large-scale empirical study. More research in this direction is needed to better understand these mechanisms. Alongside board composition as a proxy of ability, scholars might investigate how other micro-foundational factors (Aggarwal et al., 2017; Foss and Lindenberg, 2013), such as inventor networks and characteristics (Cecere and Ozman, 2014), top management diversity (Simons et al., 1999), or CEO characteristics (Crossland and Hambrick, 2011), affect the strategic decision to engage in emerging digital technologies. In addition, having presented strong arguments on the importance of the technology base for artefacts, it might be relevant to investigate outcomes related to the effect of digital reorientation of the technology base on new product development (Davila, 2003), innovation quality (Lahiri, 2010), and innovation frequency (Almeida and Phene, 2004).

In addition, we are aware of the limitations of our patent based measurement of engagement in IoT related technologies. While we rely on patent assignments to specific technology classes, future research could consider citation data to examine how emerging digital technologies are developed or used. Indeed, the open innovation literature (Enkel et al., 2009; Laursen and Salter, 2004, 2006) suggests that firms increasingly cross boundaries for technology development. Given the contemporary nature of IoT, digitalization, and open innovation, future research could build on citation data and exploit cross-citations to explore such interrelationships (Hall et al., 2001). Further, given the limitations arising from measurements with patent data in general (Ernst, 2001, 2003), future research could also consider other proxies to analyze engagement in IoT related technologies based on the nature of products and services offered by a specific firm. Furthermore, future research could engage more in determining the nature of IoT related technologies in the context of a firm's existing technology base. This would allow determining whether engagement in IoT solutions represents an exploratory or disruptive move for a specific firm in relation to its existing business model.

In view of the many contingencies that might affect firms' engagement in emergent digital technologies, we have only started to scratch the surface of the issues that need to be investigated. Nevertheless, we hope that our longitudinal examination will encourage other scholars to tackle some of the promising future research avenues, paving the way for studies at the intersection of corporate governance and business digitalization.

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