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Citation for published version

Syed, T.A. and Blome, C. and Papadopoulos, Thanos (2019) Impact of IT ambidexterity on new product development speed: Theory and empirical evidence. Decision Sciences . ISSN 0011-7315. (In press)

DOI

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Impact of IT ambidexterity on new product development speed: Theory and empirical evidence

ABSTRACT

New product development (NPD) speed is becoming an important weapon by which firms can gain market share in today's competitive and complex market environments, where consumer preferences change rapidly. Drawing on the information technology (IT)-enabled organizational capabilities perspective, this study proposes that IT ambidexterity—the simultaneous pursuit of IT exploitation and IT exploration, which has become imperative in modern industry to sustain the business value of IT—enhances NPD speed by facilitating operational agility. We examine the proposed relationship of IT ambidexterity with the potential moderating role of market complexity in a sample composed of 292 British high-tech firms. Our findings, based on a moderated-mediation analysis, suggest that the impact of IT ambidexterity on NPD speed is mediated by operational agility and that the mediation effect is especially pronounced in complex markets. The resulting theoretical arguments and empirical evidence yield further insights into the strategic impacts of IT.

Key words: IT ambidexterity, operational agility, NPD speed, market complexity, business value of IT, IT-enabled organizational capabilities

INTRODUCTION

"Secrecy and speed were found to be more important than patents for firm competitiveness in some cases, but not all." (Holgersson, 2013, p. 30)

Increasing the speed of new product development (NPD) gives firms in the high-tech industry a competitive advantage, primarily due to short product life cycles and high imitation risks (Holgersson, 2013). NPD speed reflects the time elapsed between product definition and product availability (Vesey, 1991); it capitalizes on first-mover advantage and generates higher profitability through high market shares, premium prices, higher customer loyalty and increased resource efficiency (Feng, Sun, Zhu, & Sohal, 2012). The economic turbulence and globalization of markets in recent years have challenged firms to remain competitive in an environment where a growing number of firms are chasing a dwindling number of orders from customers. An increasing number of firms rely on the strategy of rapidly introducing new products to capture market share and increase profit (Holgersson, 2013). NPD speed represents an essential factor in the success of the NPD process, and firms struggle to achieve it (Chandrasekaran, Linderman, & Schroeder, 2012; Holgersson, 2013). Therefore, it is of utmost importance to identify the mechanisms allowing firms to accelerate their NPD speed.

The role of strategic management of organizational IT resources and technological advances in enhancing NPD speed has been recognized by both researchers (i.e., Chen, Reilly, & Lynn, 2005; Pavlou & El Sawy, 2006) and practitioners. Companies such as Dell, United Parcel Service, and Cisco Systems have reduced the time-to-market by successfully developing integrated supply chain systems with real-time information transmission among suppliers, manufacturers, and customers (Rai, Patnayakuni, & Seth, 2006). Recent advances in technological solutions have identified IT ambidexterity capability that enhances a firm's ability to respond to market changes (Lee, Sambamurthy, Lim, & Wei, 2015). IT ambidexterity refers to a firm's ability to refine its existing technologies (IT exploitation) and search for new technological solutions (IT exploration) simultaneously (Lee et al., 2015). The simultaneous pursuit of IT exploitation and exploration is critical for organizational survival. For instance, Polaroid's continuous exploitation of existing analog technology without simultaneously exploring digital options resulted in a diminished market share. Although IT ambidexterity is imperative if firms in today's industries are to sustain the business value of IT, research is limited on the ramifications of IT ambidexterity in the NPD context.

Earlier information systems (IS) literature emphasized the critical role of IT capabilities in enhancing NPD speed. However, the existing literature has two gaps. First, prior studies view IT as a valuable and distinctive organizational resource that can lead to increased NPD speed (Barczak, Hultink, & Sultan, 2008; Acur, Kandemir, Weerd-Nederhof, Petra, & Song, 2010). However, the intermediating capability-building mechanisms enabling IT to translate into these competitive maneuvers have seldom been examined. For instance, previous works have considered certain direct, integrative and complementary relationships of IT tools leading to enhanced NPD speed, such as the influence of IT tool usage on speed (Barczak et al., 2008), integrating IT into supply chain operations to enhance speed (Attaran, 2004), and the complementary impacts of IT systems on operations to reduce time-to-market (Cotteleer & Bendoly, 2006). However, we need a better understanding of how IT capabilities deliver enhanced speed through organizational capability-building processes. Second, although some studies have articulated the criticality of organizational approaches to both IT exploitation and exploration (Garcia, Calantone, & Levine, 2003; Gregory, Keil, Muntermann, & Mähring, 2015; Lee et al., 2015; Mithas & Rust, 2016), studies examining the impacts of IT ambidexterity on NPD performance, i.e., NPD speed, are scarce. Instead, although prior research has focused on the general latent capabilities of IT resources—e.g., IT assets, IT investments and IT infrastructure (Barczak, Sultan, & Hultink, 2007; Acur et al., 2010) to drive NPD speed—the extant literature has neglected to explicitly conceptualize or test IT ambidexterity in this context.

Firms competing to deliver better NPD speed are often hampered by the variability of market needs and changes (e.g., industry standards, regulations, competitors, dominant designs) (Siggelkow & Rivkin, 2005; Koufteros, Rawski, & Rupak, 2010). Moreover, the growth paths for firms (i.e., global markets, venture capital) require greater information-processing resources when making decisions, resulting in slower NPD processes. To incorporate external market effects, we include the moderating effect of market complexity in our proposed model. Market complexity is defined as the extent of interdependencies among firm decisions or actions within a firm (Dess & Beard, 1984). Firms facing a more complex market will perceive greater uncertainty and have greater information-processing requirements than firms operating within a simpler market (Stoel & Muhanna, 2009). The influence of market complexity becomes particularly crucial for firms intending to deliver NPD speed; therefore, it needs to be theoretically developed and empirically tested in our investigation.

The goal of this study is to address the aforementioned research gaps by answering two key research questions: (1) How does IT ambidexterity affect NPD speed within a firm? and (2) Does market complexity influence the IT-enabled mechanism in delivering NPD speed? To answer the first question, we posit that IT ambidexterity develops operational agility, i.e., the ability to detect change and rapidly redesign operations in the firm (Sambamurthy, Bharadwaj, & Grover, 2003), as an important intermediating capability in the delivery of NPD speed. Thus, we argue that IT ambidexterity enhances NPD speed because it facilitates operational agility. To address our second research question, we examine the moderation (interaction) effects of market complexity and IT ambidexterity as well as market complexity and operational agility. We test our theory using partial least square (PLS) path modeling with a multiple respondent survey-based dataset of 292 high-tech small and medium enterprises (SMEs) in the United Kingdom (UK).

This study contributes to IS research by extending the literature on IT ambidexterity, which remains in its infancy despite its importance in today's competitive environment. This study contributes to the open debate in IS literature on whether IT constructs influence performance directly or indirectly. We extend the indirect view and draw on the capability-building perspective to reveal the underlying mechanism between IT ambidexterity and NPD speed. Finally, this study contributes to connecting the operations management and IS literature streams in two ways: (1) investigating a new set of antecedents—IT ambidexterity and operational agility—that have evolved separately in these literature streams and (2) understanding how and when IT capability interplays with organizational operations to deliver the business value of IT.

The remainder of the paper is organized as follows: In the next section, we provide a literature review and describe the development of our theoretical perspectives, followed by the study's hypotheses. Subsequently, we present the details of the data-gathering methods, the empirical analysis, and the results. Finally, we discuss the implications of this study for future research and practice.

THEORETICAL BACKGROUND AND LITERATURE REVIEW

This study draws on ambidexterity and IT-enabled organizational capabilities perspectives to conceptualize our theoretical model. The elements of the model's conceptual development are described in the following sections.

IT ambidexterity

Ambidexterity refers to the ability of a person to work with both hands with equal ease. This concept is increasingly used in organizations to represent the ability of the firm to balance differing and often competing trade-offs. Organizational learning theorists identify this trade-off as

consisting of the exploitation and exploration enabling organizations to leverage their resources and capabilities (March, 1991; Levinthal & March, 1993). Exploitation refers to the efficiency, refinement, and enhancement of existing organizational resources through known processes, whereas exploration relates to searching for, experimenting with and innovating with potential resources to create new capabilities and opportunities (March, 1991). Prior literature acknowledges exploitation and exploration as two distinct activities managed through trade-off, in tandem, or through complementarity approaches.

The trade-off approach advocates specializing in either exploration or exploitation (March, 1991); however, exploitation alone lacks the flexibility to adapt to changes, and exploration alone lacks the efficiency to harvest new ideas (Benitez, Llorens, & Braojos, 2018b). The tandem approach describes the sequential pursuit of exploitation and exploration by temporal separation (Gupta, Smith, & Shalley, 2006). However, it becomes challenging to shift the momentum of one activity to start a completely different other activity. Moreover, excessive reliance on exploitation for short-term performance may lead to a "competency trap" in which exploitation drives out exploration, and excessive focus on exploration may lead to a "failure trap" in which exploration drives out exploitation (Levinthal & March, 1993). The complementarity perspective, also referred to as the ambidexterity perspective, suggests that a synergistic effect occurs when both activities are pursued simultaneously (Gibson & Birkinshaw, 2004; He & Wong, 2004). To pursue exploration and exploitation in a balanced way so they complement each other is highly desirable if firms are to sustain a long-term competitive advantage (Raisch, Birkinshaw, Probst, & Tushman, 2009). Although hard to achieve, reconciling and harnessing such a combined and simultaneous pursuit of these contradicting activities effectively improves firm performance (Raisch et al., 2009; Im, Rai, & Lambart, 2019).

Different literature streams—including innovation management, organizational learning, strategy, and organizational theory—have contributed to research on organizational ambidexterity. The main contributions to the ambidexterity literature have been made within the innovation ambidexterity research stream, focusing on exploratory and exploitative innovations (i.e., He & Wong, 2004; Jansen, Van Den Bosch, & Volberda, 2006). The same concept has recently emerged in IS research, where IT ambidexterity is defined as the firm's ability to undertake both exploitation and exploration of IT resources and practices (Lee et al., 2015; Mithas & Rust, 2016). IT exploitation refers to the continuous improvement of existing technological practices, whereas IT exploration is associated with introducing novel and innovative technological solutions (Lee et al., 2015). Intense competition, fast-changing technologies, and globalization in today's industries require firms to exploit and explore their IT resources to sustain IT-based competitive advantage. However, limited attention has been paid to understanding and investigating the implications of IT ambidexterity. Table 1 presents a comprehensive overview of the extant literature relevant to IT ambidexterity. This study differs from prior research by investigating IT ambidexterity in the context of NPD, particularly in high-tech firms, where an accelerated NPD speed represents the success of the NPD process (Chandrasekaran et al., 2012; Holgersson, 2013).

Authors	Theoretical lens	Methodology	Key finding(s)
Gregory et al. (2015)	Paradox and ambidexterity theory in an IT transformation program	A longitudinal study of an IT transformation program in a commercial bank	Identifies and explains six paradoxes that managers face in IT transformation programs: (1) IT portfolio decisions (i.e., IT efficiency versus IT innovation), (2) IT platform design (i.e., IT standardization versus IT differentiation), (3) IT architectural change (i.e., IT integration versus IT replacement), (4) IT program planning (i.e., IT program agility versus IT project stability), (5) IT program governance (i.e., IT program control versus IT project autonomy), and (6) IT program delivery (i.e., IT program coordination versus IT project isolation).

Table 1: An overview of the extant research on IT ambidexterity

Lee et al. (2015)	Capability- building perspective	A survey study of 178 business and IT executives	IT ambidexterity enhances organizational agility by facilitating operational ambidexterity, and the magnitude of the facilitation depends on the level of environmental dynamism.
Mithas & Rust (2016)	IT strategic orientation and the resource- based view	A secondary dataset of more than 300 firms	An IT ambidextrous strategy (dual emphasis of IT resources in revenue expansion and cost reduction) strongly moderates the influence of IT investments on performance (profitability and market value) at high levels of IT investments.

IT ambidexterity and NPD speed

Acur et al. (2010) find that a firm's technological competence (i.e., the ability to seize and reconfigure IT resources) enhances NPD speed, whereas technological alignment has a negative effect on NPD speed. The work of Acur and her colleagues is intriguing because it shows that the two distinct but necessary traits of IT activities lead to opposing outcomes in NPD performance. However, Acur's work leaves open the question of how NPD speed will be impacted by a balanced approach (IT ambidexterity) to such opposing IT activities.

Another major gap in the extant IS literature is that it has focused primarily on the effects of IT as an asset, an artifact, or a tool, instead of as a capability for enhancing the operational or process efficiency of NPD processes (i.e., Cotteleer & Bendoly, 2006; Pavlou & El Sawy, 2006; Acur et al., 2010). This approach has resulted in mixed findings regarding the impact of IT on NPD speed. For example, Pavlou & El Sawy (2006) measured NPD speed as a process-efficiency indicator and found a positive relationship between IT-enabled NPD activities and process efficiency, whereas Barczak et al. (2007) report a statistically nonsignificant impact of IT usage on NPD speed in American and Canadian firms. In another study, the same authors found that IT usage significantly impacts NPD speed in a sample of Dutch firms (Barczak et al., 2008). The inconsistencies among the results suggest a need for a thorough investigation of this link. Table 2 provides an overview of the research on the influence of IT on NPD speed.

Given these competing perspectives on IT exploitation and IT exploration as well as the absence of empirical research to resolve this dispute, the current study seeks to determine whether IT ambidexterity helps or hurts NPD speed. This study differs from prior research in several ways: First, we focus on IT ambidexterity—a higher-order IT capability composed of two distinct IT activities. Second, we investigate the link between IT ambidexterity and NPD speed in a granular fashion by highlighting operational agility as a mediating IT-enabled organizational capability allowing firms to leverage their IT resources in enhancing NPD speed.

Author	Context/Research	Theoretical	Methodology	Key arguments and findings
	focus	lens		
Attaran (2004)	Influence of IT on process design to assist NPD speed	Strategic IT integration	Theoretical development	IT helps firms initiate and sustain business process re-engineering as an enabler before process design, as a facilitator during process design, and as an implementer after process design. IT assists positively in reducing the average operational cycle time for firms.
Barczak et al. (2007)	Influence of IT embeddedness, project risk and champion on IT tools usage to impact NPD speed	IT use in NPD	Empirical analysis using a survey of 212 US and Canada Product Development & Management Association (PDMA) members	Project risk, the existence of a champion, and IT embeddedness positively affect the extent of IT usage for NPD. Additionally, IT usage positively and significantly influences the performance of the new product in the marketplace. IT usage does not have any impact on NPD speed.
Barczak et al. (2008)	Influence of IT embeddedness and process formalization on IT tools usage to enhance NPD speed	Hofstede's theory of culture	Empirical analysis using a survey of 212 US PDMA members and 118 Dutch NPD managers	In the United States, IT embeddedness, NPD process formalization, and the outsourcing of NPD projects positively influence IT usage. In the Netherlands, IT embeddedness and NPD process formalization have a positive impact on IT usage. IT usage positively influences NPD speed in the Netherlands and market performance in the United States.
Acur et al. (2010)	Influence of IT alignment and technological competence development on NPD speed	Dynamic capabilities approach	Empirical analysis using a survey of 164 firms	Technological alignment (the extent to which technological developments guide a firm's NPD activities) was negatively related to NPD speed, whereas technological competence development (ability to acquire, integrate, and reconfigure technological knowledge) positively affected NPD speed.

Table 2: Comprehensive overview of the extant research on IT's influence on NPD speed

Organizational capability-building perspective

The capability-building perspective refers to the mechanisms through which firms integrate and reconfigure internal and external resources to develop competitive capabilities (D'Aveni, Dagnino, & Smith, 2010). IT-enabled organizational capabilities extend the capability-building perspective by understanding how IT enables intermediating organizational capabilities to generate value for the firm (Mithas, Ramasubbu, & Sambamurthy, 2011). Consistent with this conceptualization, IS researchers have examined the business value of IT through IT-enabled mechanisms helping firms develop competitive actions, such as online consumer engagement (Braojos, Benitez, & Llorens, 2018), IT-enabled operational ambidexterity (Lee et al., 2015), IT-enabled knowledge ambidexterity (Benitez, Castillo, Llorens, & Braojos, 2017), IT-enabled business flexibility for sensing and seizing merger and acquisition (M&A) opportunities, and IT-enabled post-M&A integration capability for realizing economic benefits (Benitez, Ray, & Henseler, 2018c).

Prior studies have analyzed IT-enabled intermediating mechanisms to investigate the link between IT and NPD speed. For example, Attaran (2004) finds that IT initiates process reengineering to facilitate process design and reduce the average time-to-market. Similarly, Acur et al. (2010) observe that IT alignment enables technological competency, allowing firms to enhance the NPD speed of their products. Table 2 (second column) provides information about the intermediating mechanisms between IT and NPD speed as discussed in the extant research. However, prior studies that have investigated IT's impact on NPD speed have mostly focused on IT-related factors only (i.e., IT embeddedness impacts IT tool usage to affect NPD speed (Barczak et al., 2007), or IT alignment develops technological competency to help NPD speed (Acur et al., 2010)). Our study differs from prior studies by examining how IT capability (IT ambidexterity) facilitates the development of operational capabilities (operational agility) as an intermediating mechanism to increase NPD speed. Thus, we contribute to the IS literature by explaining how IT ambidexterity translates into delivering NPD speed through IT-enabled operational mechanisms, as our understanding of this issue remains limited.

IT-enabled organizational capability for NPD speed

To address the research gap discussed previously, we focus on operational agility as a key ITenabled organizational capability allowing a firm to enhance the NPD speed of new products. Operational agility, defined as the ability to rapidly detect and redesign existing processes to exploit dynamic marketplace opportunities quickly, accurately and cost-efficiently, is critical for achieving excellent NPD speed because operational agility depends on a firm's reaction to market changes (Sambamurthy et al., 2003). For instance, the classical built-to-order operational model used by Dell can be thought of as an example of an agile operational capability responding swiftly to fastchanging end-user preferences. However, such constant reconfiguration of business operations requires technological support (Tallon & Pinsonneault, 2011; Benitez et al., 2018c). Recognizing that operational agility is driven by technology, IS researchers have tended to conclude that a firm could strengthen its operational agility by leveraging its IT capability (Chen, Wang, Nevo, Jin, Wang, & Chow, 2014; Tan, Tan, Wang, & Sedera, 2017; Benitez et al., 2018c). Particularly for firms in the high-tech or fashion industries, where change is both expected and regular, IT ambidexterity has emerged, next to operational agility, as an imperative to avoid rigidity traps (Lee et al., 2015). However, the respective literature on IT ambidexterity capability and operational agility have evolved separately. Therefore, we seek to combine and understand the link between IT ambidexterity and operational agility in an NPD context. In doing so, we examine the mediating role of operational agility in the relationship between IT ambidexterity and NPD speed. Table 3 presents the definitions of our key constructs and respective case examples.

Key constructs	Operationalization and supporting literature	Source	Case example
IT ambidexterity	IT ambidexterity is conceptualized as a firm's ability to pursue both IT exploitation and IT exploration simultaneously.	Lee et al. (2015), Mithas & Rust (2016),	Merrill Lynch's utility model simultaneously leveraged both IT exploration and IT exploitation for its cost-effective yet flexible IT service provisioning (Lee et al., 2015).
Operational agility	Operational agility represents the ability to rapidly detect dynamic marketplace opportunities and redesign existing processes quickly, accurately, and cost-efficiently for competitive actions. Additionally, our definition of operational agility reflects the similar concept known as business flexibility, which refers to the "capability to sense and seize business opportunities by changing factors of production and operational processes" (Benitez et al., 2018c, pg. 27).	Sambamurt hy et al. (2003), Benitez et al. (2018c)	Zara's agile supply chain operations enabled the company to rapidly spot possible trends. Doing so gave them a head start over competitors because fabric suppliers require long lead times (Lee, 2004).
NPD speed	NPD speed is referred to as the time elapsing between product definition and product availability. Although different terms such as time-to-market, cycle time, or innovation speed are used, all capture the similar concept of NPD speed (Chen et al., 2005). NPD speed should not be confused with responsiveness, as the latter refers to the quickness with which firms respond to a change (Zaheer & Zaheer, 1997), while the former is the quickness with which firms develop an idea from conception to a product (Chen et al., 2005).	Vesey (1991), Chen et al. (2005), Chandrase karan et al. (2012)	3D printers used by Alcoa have compressed its prototyping time from months to hours, making products available to customers in a short time. Similarly, Fiat slashed an eight-month prototyping process to one week through digitized operations, thus expediting the NPD speed of new products (George, Ramaswamy, & Rassey, 2014).

Table 3: Definitions, sources and case examples of key constructs

IT ambidexterity, market complexity, and NPD speed

Firms operate within external markets that often influence their strategies for and constraints on performance (Des & Beard, 1984). Thus, the relationship between IT ambidexterity and NPD speed may be contingent on a firm's market context. In particular, higher interdependencies among firm activities may compromise a firm's tendency to deliver NPD speed (Harter, Krishnan, & Slaughter, 2000). Market complexity captures the diversity of the product range that a firm offers (Stoel & Muhanna, 2009). Although market complexity has been identified as a critical factor hampering NPD speed (Siggelkow & Rivkin, 2005; Koufteros, Rawski, & Rupak, 2010), existing research seldom examines its effects on the IT and operational capabilities delivering NPD speed.

Des & Beard (1984) theorize complexity as the heterogeneity among a range of inputs and outputs, whereas Pfeffer & Salancik (1978) posit that complexity is the number of external actors that a firm actively interacts with for survival. However, both authors contend that firms operating in situations of higher market complexity will perceive greater uncertainty and require greater information processing than firms facing simpler markets. Such an increase in information processing and interdependencies may escalate the importance of IT capabilities, but it may simultaneously adversely affect NPD speed. For instance, Pavlou & El Sawy (2006) found that higher uncertainty and turbulence exerted a positive moderating influence on the impact of IT on dynamic NPD capabilities while negatively moderating the impact of IT on NPD performance measures. Thus, it is important to theoretically develop and empirically test the effects of firms' interdependencies on NPD performance measures (i.e., NPD speed) that may otherwise bias our results. Accordingly, we include the moderation (interaction) effect of market complexity in our proposed relationships. Figure 1 presents the proposed conceptual model of our study.



HYPOTHESIS DEVELOPMENT

IT ambidexterity and operational agility

The simultaneous pursuit of IT exploitation and IT exploration ensures the efficient use of existing technology to access data across units and simultaneously strives to innovate technological practices to capture real-time market data to adjust a firm's actions accordingly (Lee et al., 2015; Mithas & Rust, 2016). IT ambidexterity thus enables firms to digitally transform their business processes to achieve operational flexibility and uplift quality. For example, Haier Group, which started as an importer of refrigerator production technologies, leveraged IT exploitation and IT exploration at the same time, enabling operational agility such that Haier Group evolved as a global appliance company with ninety-six product categories (Huang, Ouyang, Pan, & Chou, 2012). In addition to the continued emphasis on improving existing technologies to digitize procurement and supply chain systems to match the pace of Haier's fast expansion, the firm implemented an innovative Global Value System (GVS). GVS was able to achieve process synchronization and check the alignment between the requirements and constraints of different departments so that the outcomes of planning were accurate and feasible. This operational enhancement to synchronize information facilitated operations to sense market trends and respond to competitive actions in time, enabling the firm to achieve superior operational maneuverability. Haier's ability to simultaneously undertake both IT exploration and IT exploitation demonstrated an improvement in operational agility (Huang et al., 2012).

IT ambidexterity strengthens a firm's ability to develop potentially disruptive ways of using operational resources that proactively create change rather than merely react to it. A lack of appropriate IT capabilities makes it difficult for firms to adjust to changing market conditions, resulting in passive and slow responses when seeking new strategies (Overby, Bharadwaj, & Sambamurthy, 2006; Tallon & Pinsonneault, 2011). IT ambidexterity capability directly influences

a firm's operational agility factors, enabling it to sense a market change and respond to it. Specifically, IT exploration expands the firm's boundaries so that the firm can connect with external knowledge sources, which better equips the firm to sense changing market trends and to capture new opportunities. Thus, IT exploration may help firms learn of any major technology breakthroughs in a timely fashion, allowing firms to stay ahead of their competition and evade the competency trap (Raisch et al., 2009). On the other hand, IT exploitation fosters routines that can leverage existing technology and knowledge repositories efficiently, which swiftly incorporates changing trends or captures new opportunities by extending relevant knowledge pools already present in a firm (Benner & Tushman, 2003). Together, IT exploration and IT exploitation foster mobility, transformability, and flexibility in firm operations by helping firms evolve externally and integrate new technology internally, respectively. For example, Zara, a leader in the world of fashion, consistently improves its operational agility through continuous improvement of existing technologies to collect real-time data while simultaneously investing in sophisticated IT systems to build shared situational awareness (making sense of real-time data from multiple sources) (Lee, 2004). Hence, we propose the following:

H1: There is a positive relationship between IT ambidexterity and operational agility.

Operational agility and NPD speed

Operational agility equips firms to rapidly sense market changes, which allows them to reconfigure existing processes in time to meet changing demands and earn profits, increase their market share and gain customers (Yusuf, Sarhadi, & Gunasekaran, 1999). Thus, operational agility assures firms of higher NPD speed in the face of changing demand, trends, or market forces. Kumar & Motwani (1995) suggest that operational agility gives firms the ability to accelerate activities on the critical path and generate time-based competitiveness. We can infer that operational agility assists firms in building NPD speed by enabling them to sense and respond proactively to changing market demands, i.e., delivering new products ahead of competitors and making products available just before the need arises. For example, Dell consistently polished its capability to respond to market changes through a strategy of operational segmentation allowing it to gain competitiveness over Compaq and Hewlett-Packard (Lee, 2004). The user-specific configurations of personal computers are produced and delivered within weeks of the order being received.

Operational agility pertains to the capability integrating firms' internal operations with external conditions, i.e., to adapt or respond rapidly to market changes as well as to potential and actual disruptions, thus both enhancing existing customers' loyalties and creating new customers via proactive product deliveries. This capability is particularly evident among firms in the high-tech and fashion industries, where internal actions largely depend on external market conditions such as changing trends, supplier price changes, fluctuations in customer demand, technological breakthroughs or government policies (Oke, Burke, & Myers, 2007). Firms with the operational capability to sense and respond to such conditions in a timely fashion do not compromise NPD speed and gain larger market share (Overby et al., 2006; Tallon & Pinsonneault, 2011). In addition, firms that have digitalized their operations are now able to achieve higher agility and enhanced NPD speed, such as Alcoa and Fiat. With the 3D printing and advanced aluminum investment casting, Alcoa and Fiat have simplified physical prototyping time, slashing an eight-month physical prototyping process to one week (George et al., 2014). Hence, we propose the following:

H2: There is a positive relationship between operational agility and NPD speed.

The mediating role of operational agility in the relationship between IT ambidexterity and NPD speed

While IT exploitation leads to efficiency and stable existing technology in a firm's actions, IT exploration reinforces existing technology through continuous upgrading with new technological breakthroughs. In this way, IT ambidexterity helps firms escape stagnation and improves NPD processes such as NPD speed. However, the findings of Acur et al. (2010) suggest that the direct impact of a continuous process involving the acquisition, integration, and reconfiguration of technological knowledge (i.e., IT exploitation) may enhance NPD speed, while technological developments (i.e., IT exploration activities) impede NPD speed. We argue-in concert with Lee et al. (2015)—that while the cross-sectional impact may be suppressive when simultaneously pursuing IT exploitation and exploration activities, the long-term effect of IT ambidexterity will build operational capabilities through the complementary influences of IT exploration and exploitation activities. To capture this effect, we focus on the capability-building perspective of IT ambidexterity rather than the direct effect. Moreover, the research argues that the direct impact of IT capabilities on performance measures may not be the right approach to measure the significance of IT capabilities (Devaraj & Kohli, 2003; Nambisan, 2013). Based on the resource-based view (RBV) and the IT-enabled organizational capabilities perspective, IS scholars acknowledge that the true competitive potential of IT resources or capabilities can be better realized through a firm's internal operations (Tippins & Sohi, 2003; Lee et al., 2015; Benitez et al., 2018c). In this theory, much of the business value of IT stems from its complementarities with business processes (Overby et al., 2006). Thus, we suggest that this is also the case for the relationship between IT ambidexterity and NPD speed, such that operational agility mediates the effect of IT ambidexterity on NPD speed.

IT ambidexterity indirectly supports NPD speed by enabling operational agility in firms. IT ambidexterity as a digital platform supports operational processes in adapting to changing requirements quickly by capturing information-based value propositions, forging value-chain collaborations with partners that competitors cannot easily duplicate, and rapidly exploiting emerging and untapped market niches (Lee et al. 2015). Consequently, a firm's operational flexibility drives NPD speed by sensing changes in market demand and responding proactively to them in many physical operations, including design, manufacturing, testing, and transportation. A basic premise of this proposition is that IT ambidexterity enhances the richness and reach of a firm's knowledge base and its operations (Lee et al., 2015). IT exploration enhances the quality of information (richness) by providing firms with high-quality information that is timely, accurate, descriptive, and customized for incorporation into firms' operations. IT exploitation assists firms in extending their operational range (i.e., reach) by providing an array of possibilities to access, synthesize, and exploit knowledge from a wide range of sources. Together, increases in the quality of information and the range of possibilities improve a firm's operational ability to sense and respond to changing demands, thereby reducing the developmental time required for new products. For example, IT integration in the global currency trading industry harnesses the richness and reach of firms' operations to act quickly and proactively to obtain private price information (Overby et al., 2006). This ability allows firms to deliver rapid responses to changes in customer needs, competitors, and technology or regulatory developments. IT ambidexterity creates operational agility by extending operational reach and richness so that firms are better integrated internally and informed externally so that they can deliver high NPD speed. Hence, we propose the following:

H3: Operational agility mediates the relationship between IT ambidexterity and NPD speed.

The moderating role of market complexity

Market complexity represents the heterogeneity of product offerings and the level of knowledge sophistication of a system with multiple interdependencies (Dess & Beard, 1984). The market

complexity or the level of knowledge sophistication increases as the firm grows, i.e., has a greater number of suppliers, joint ventures, internationalization strategies or mergers and acquisitions (Stoel & Muhanna, 2009). These elements may influence the impact of IT ambidexterity on facilitating operational agility and the relationship between operational agility and NPD speed. We argue for an interaction effect of (1) IT ambidexterity and market complexity and (2) operational agility and market complexity on NPD speed.

The level of market complexity depends on the number of products offered by the firm, the operating industry, the level of knowledge sophistication firms must have about the products and their consumers, and the number of external actors who must be influenced for the firm to be successful (Chen et al., 2014). Firms facing higher levels of market complexity will perceive greater uncertainty and have greater information-processing requirements (Pfeffer & Salancik, 1978; Dess & Beard, 1984). This observation is consistent with the information-processing view (Galbraith, 1974), in which decision-makers faced with uncertain tasks require more information to achieve higher performance. The influence of both IT ambidexterity and operational agility is likely to be stronger in highly complex markets. Firms operating in these market conditions require superior IT capabilities to collect, process, and assimilate complex external information and to formulate and coordinate with firm operations. IT ambidexterity might become more of a necessity for firms to transform the information collected into operational maneuvers. For instance, even in a situation of high market and product complexity (over 1,000 configurations), Dell's operational capabilities maintain NPD speed by rapidly redesigning operations based on market information (Lee, 2004). Similarly, complex market conditions require superior operational capabilities to enhance operational reach and richness, both of which help firms accommodate changes in customer needs, competitors, and technology or regulatory developments, allowing firms to deliver new products that meet changing market demands on time. Consequently, IT-enabled operational agility becomes a significant contributor to ensure enhanced NPD speed. For example, in the aftermath of the 1999 earthquake in Taiwan, Dell's agile operations were able to deliver reliably and quickly, enabling the company to gain market shares by collecting informational data on the earthquake damage early, thus gaining a competitive edge over rivals such as Compaq, Apple and Gateway (Lee, 2004).

In contrast, lower levels of market complexity are characterized by stable markets and lower interdependencies. Firms operating in such environments mostly rely on producing homogeneous products and require low information processing (Chen et al., 2014). In these conditions, firms can leverage more stabilized and well-developed practices (Stoel & Muhanna, 2009; Lee et al., 2015). Therefore, in a situation of low market complexity, dynamic capabilities such as IT ambidexterity and operational agility are less of a necessity and offer fewer potential benefits (Tallon & Pinsonneault, 2011). Stable settings offer fewer occasions to exercise these options; thus, the likelihood is lower that lower market complexity will complement the influences of IT ambidexterity and operational agility. In summary, firms with greater market complexity may benefit from the stronger influences of IT ambidexterity and operational agility as opposed to firms in simple markets, where there are fewer opportunities to exercise these capabilities. Hence, we propose the following:

H4a: Market complexity will positively moderate the relationship between IT ambidexterity and operational agility.

H4b: Market complexity will positively moderate the relationship between operational agility and NPD speed.

RESEARCH METHODOLOGY

Empirical context and data collection

The target population for this study consisted of British high-tech SMEs (up to 249 employees) registered in the Financial Analysis Made Easy (FAME) database, which provides the most comprehensive listing of UK companies and contact information, including firms listed and unlisted on the London Stock Exchange. The population covers a wide range of high-tech SMEs involved in new product/service development projects. Specifically, we included firms in computer and electronic product manufacturing, control instrument manufacturing, telecommunication, medical equipment and supplies manufacturing, and optics, all of which are included in the NAICS 2012 industry classification under codes 33, 51 and 54. Our sample consisted of 1,000 firms that had been in operation for at least three years by 2015.

The rationale for focusing on SMEs is that they represent a key segment of all major industries and are drivers of national economies (Oke et al., 2007). For instance, the British government claims that SMEs account for 99.9% of all enterprises in the UK, as opposed to large enterprises (more than 249 employees), which account for 0.1% of enterprises but 40.9% of employment and 51.4% of turnover (Department for Business Innovation Skills, 2011). Moreover, in contrast to large firms, SMEs make it easier to accurately measure intricate constructs (i.e., market complexity, IT ambidexterity) and to clearly observe performance implications. High-tech is one of the most rapidly evolving sectors among SMEs (Oke et al., 2007; Holgersson, 2013). Consequently, many governments have been taking initiatives to support the growth of this sector. In particular, the British government has placed significant emphasis on promoting the high-tech industry through initiatives such as the GovTech Catalyst, Tech Nation, the Global Innovation Program, and Living Innovation (Oke et al., 2007). The British government reports that 13.4% of SMEs operate in the high-tech sector, with a 74.7% share of employment and 65.7% share of turnover, which represents a quarter of all UK SMEs (Department for Business Innovation Skills, 2011), making the UK, apart from the USA and Taiwan, one of the most important supply centers of high-tech products in the world (Oke et al., 2007; Tsai & Yang, 2013). Ranking 4th among world innovation enablers in the 2018 Global Innovation Index report (Dutta, Lanvin, & Wunsch, 2018), UK high-tech SMEs provide a rich context in which to examine NPD outcomes. Focusing particularly on high-tech SMEs also contributes to reducing the potential variance caused by the industry effect (Tsai & Yang, 2013), thus allowing us to better investigate our research questions.

We used a survey questionnaire as the data collection instrument to test our hypotheses. In an effort to improve content validity and response rates, the survey questionnaire was designed, formulated, and implemented in a manner closely following the recommendations of Podsakoff, MacKenzie, Lee, & Podsakoff (2003). After finalizing the questionnaire, IT executives or project managers were contacted and asked to identify appropriate respondents within their firms who could complete other sections of the questionnaire, i.e., a project manager to complete the NPD speed and market complexity sections, an operations manager to complete the operational agility section, and an IT executive to complete the IT ambidexterity section. Consequently, each questionnaire was completed by three respondents within the same firm. Asking senior managers to distribute the surveys helped in identifying appropriate respondents, and this method is consistent with prior IS studies. The specific criteria questions were set in the online questionnaire to further confirm and allow access only to relevant respondents for each section. In this sense, we used multiple respondents for each questionnaire to minimize the appearance of common method bias (Podsakoff & Organ, 1986). The respondents were contacted by telephone and e-mail before we sent them the link to an online questionnaire. Follow-up telephone calls and two reminder emails were sent to the nonrespondents after the third and fifth weeks. After fourteen weeks, 317 responses were collected. Upon removing 25 unusable responses, 292 valid responses remained with complete information for the variables of interest, representing a 29.2% response rate. Our key respondents had worked for 4.5 years in their firms on average, and 70.4% of these respondents had a university degree. Therefore, respondents were able to understand all the items and respond accurately. We tested for differences in respondent types; one-way analyses of variance (ANOVAs) were performed with all of the major constructs as dependent variables and respondent type as the independent variable using SPSS 22.0. No significant differences were found. Table 4 presents the characteristics of our respondent firms.

		Frequency	Percentage
	Computer and peripheral equipment	94	32.2
	Communications equipment	47	16.1
Industry	Semiconductor and electronic components	78	26.7
	Medical equipment and supplies	32	11.0
	Industrial and precision equipment	41	14.0
Sino	Small (1 to 49 full-time employees)	160	54.8
Size	Medium (50-249 full-time employees)	132	45.2
	Fewer than 5 years	35	11.9
1.00	Between 5 and 10 years	71	24.3
Age	Between 10 and 15 years	84	28.8
	More than 15 years	102	34.9
Tuno	Service	161	55.1
Type	Manufacturing	131	44.9

Table 4: Characteristics of respondent firms

To calculate the minimum required sample size, a pretest of a statistical power analysis was conducted with an anticipated medium effect size ($f^2 = 0.150$), a desired statistical power level of 0.95, six predictors (i.e., the number of structural links received by the NPD speed) and a confidence level of 0.01. The test revealed that the proposed model required a minimum sample

size of 189 (Cohen, 1988). Our sample size of 292 suggested that our study had sufficient statistical power to detect significant effects (Cohen, 1988).

We compared the patterns of respondents with nonrespondents to test for nonresponse bias, and we compared the patterns of early and late respondents to assess late-response bias in our sample. The results of t-tests revealed that the respondents and nonrespondents did not differ statistically in terms of firm size (p > 0.05), firm age (p > 0.05) and industry type (p > 0.05). Industry types were classified as service firms and manufacturing firms based on the industry classification under the NAICS 2012. Similar results were found when comparing early and late respondents. The findings of these comparisons suggested that nonresponse bias and late-response bias are unlikely to be issues in our data.

Measures

All measures in the study were evaluated at the firm level and were based on well-established scales in the literature. Every attempt was made to use validated measures with good psychometric properties, although we made some modifications to suit the context of our research. All items were based on five-point Likert scales with 1 indicating "strong disagreement" and 5 indicating "strong agreement" with the statements. Understanding the nature of the relationship between constructs and measures is an essential aspect of measurement specification. Two types of measurement constructs can be distinguished: latent variables, which the existing literature proposes to operationalize as reflective or causal-formative measurement models (Benitez-Amado, Henseler, & Castillo, 2017; Bollen & Diamantopoulos, 2017), and artifacts, which have been recently referred to in empirical IS research as composite constructs (e.g., Benitez et al., 2018b). Reflective constructs assume that the existence of one unobserved variable and individual random error perfectly explains the variance of a set of indicators (Henseler, Dijkstra, Sarstedt, Ringle, Diamantopoulos, Straub et al., 2014; Dijkstra & Henseler, 2015). Such models can be used to measure behavioral concepts—i.e., personality traits, individual behavior, and individual attitudes—that frequently appear in the theoretical constructs of behavioral sciences (Henseler, Hubona, & Ray, 2016). In contrast, composite constructs do not impose any restrictions on the covariance among indicators of the same construct, thereby relaxing the assumption that all the covariation among a block of indicators is explained by a common factor (Benitez et al., 2017). Composites are usually behavioral constructs, consisting of more elementary components. These composites serve as representatives for the concept under investigation and can be seen as a mix of ingredients (indicators/dimensions) to create the recipe (composite) (Dijkstra & Henseler 2015; Henseler et al., 2016; Rueda, Benitez, & Braojos, 2017). Based on the aforementioned criteria, we discussed our constructs with senior academics in IS and, based on their consensus, operationalized all constructs of our proposed model as composite constructs at both the first- and second-order levels.

IT ambidexterity. IT ambidexterity represents the simultaneous approach of firms in pursuing IT exploitation and IT exploration activities; therefore, it is measured as the combination of these activities. IT ambidexterity was operationalized as a composite second-order construct determined by a four-indicator composite first-order construct of IT exploitation and a five-indicator composite first-order construct of IT exploitation was measured by adapting the scale evaluating the competency of the firms to refine their existing IT system quality, expand their existing IT services, and extend their current IT operations. IT exploration was measured by adapting the scale datapting the scale capturing the competency of the firm to introduce new technology applications, a new range of informational services, and new IT practices when compared with its industry. The

measures of IT exploitation and IT exploration were adapted from the studies of Lee et al. (2015) and Jansen et al. (2006).

Operational agility. Operational agility was measured by a first-order three-indicator composite construct. The three-item scale reflects the ability of organizational internal processes to physically and rapidly cope with and respond to changes in market or customer requirements. The measuring scale was adopted from the study of Lu & Ramamurthy (2011).

Market complexity. The first-order four-indicator composite construct operationalized market complexity. The four-item scale was adopted from the study of Chen et al. (2014) measuring complexity in terms of the heterogeneity (diversity in customers' buying habits and product lines) and range of an organization's activities resulting from a frequent change in suppliers and legal regulations.

NPD speed. Because we used a multi-industry (manufacturing and service) sample, we tried to control for NPD speed differences in the nature of projects by using a relative NPD speed measurement scale, which we aggregated with archival data. The relative NPD speed approach and items used to measure it were adapted from Kessler & Chakrabarti (1999) and Chen et al. (2005). The four-item scale was used to assess the NPD speed of new product or service introduction, comparing actual performance with pre-set schedules, company standards and similar competitive projects. The archival data consisted of the number of months elapsed from concept to market launch relative to firm objectives as documented in that firm's records (McNally, Akdeniz, & Calantone, 2011). The archival data were scored and sorted into three categories (0 = far below expectations, 2.5 = meeting expectations and 5 = far above expectations). To ensure data reliability and to reduce the risk of any confounding effects of common method bias in our data, we used SPSS 22.0 to aggregate the score based on agreement values (r_{wg}) and interclass correlation

coefficients (ICC) between survey and archival data. We examined agreement against the uniform null distribution and found a value of 0.88, indicating strong agreement. ICC values were 0.79, indicating high agreement. Table 5 displays the aggregation statistics, which offer strong support for aggregation (LeBreton & Senter, 2008).

Variable	r _{wg}	One-way ANOVA	ICC
NPD speed	0.88	9.144***	0.79

Table 5: Tests to aggregate survey and archival responses for NPD speed

**** p < 0.001

Control variables. We controlled for the effects of the size of the firm, the age of the firm, and the industry on NPD speed. These contextual factors are well recognized and are commonly used as control variables. Firm size represents the resource availability and may drive a firm to develop new products more quickly to seize the moment from a competitor or to respond quickly to a competitor's new product (Stoel & Muhanna, 2009; Chen et al., 2010). The size of the firm was measured as the natural logarithm of the average number of full-time employees in the firm. Firm age controls for a firm's experience developing similar projects or the degree of prior experience and knowledge in the NPD process (Chen et al., 2010). Firm age was measured as the natural logarithm of the total number of years the firm had been in business. Similarly, the nature and significance of IT-driven processes and their impacts may differ across industries and new product types, so industry was considered an important contextual variable (Stoel & Muhanna, 2009). An industry variable was operationalized with a dummy variable of 0 for manufacturing firms and 1 for service firms.

EMPIRICAL ANALYSIS AND RESULTS

We performed PLS path modeling to test our hypotheses in our proposed model. PLS is an appropriate choice for the estimation method for the following reasons. First, PLS is suitable for estimating composite models (Benitez et al., 2017; Benitez et al., 2018c). Second, PLS provides estimations of complex models with both second- and first-order level composite constructs (Hair, Sarstedt, Ringle, & Mena, 2012; Braojos-Gomez, Benitez-Amado, & Llorens-Montes, 2015). Finally, PLS does not impose any normality requirements on the data and tests for exact model fit (Henseler et al., 2016). We used the latest statistical tool, Advanced Analysis for Composites (ADANCO) 2.0 Professional, by Henseler & Dijkstra (2015). ADANCO is a contemporary variance-based SEM software facilitating both causal and predictive modeling (Benitez et al., 2017; Benitez et al., 2018c).

Measurement model evaluation

The methods of evaluation for measurement and the structural model may differ with respect to the nature of the relationships (i.e., composite or reflective) between measures and constructs (Jarvis, MacKenzie, & Podsakoff, 2003; Benitez-Amado, Llorens-Montes, & Fernandez-Perez, 2015). As detailed previously, all the constructs in this study were characterized as composite constructs. Thus, we assessed the psychometric properties of our first- and second-order composite constructs by content validity, multicollinearity, weights and loadings because the traditional assessments of validity and reliability (i.e., composite reliability, average variance extracted and Cronbach's alpha) may not apply well to composite constructs (Petter, Straub, & Rai, 2007).

We calculated the variance inflation factors (VIFs) at both the first- and second-order levels to examine multicollinearity. VIFs higher than 10 indicate a multicollinearity issue (Thatcher & Perrewe, 2002). Our results reveal that the VIF scores range from 1.653 to 3.536, suggesting that multicollinearity is not a problem in our data.

We used a bootstrap analysis with 5,000 subsamples, which is well recommended and commonly used in a PLS analysis to estimate the significance of loadings, weights and path coefficients (Benitez-Amado et al., 2015; Benitez-Amado et al., 2017). The analyses reveal that all the indicator weights and loadings were significant except for the weight of one indicator of market complexity. This composite indicator was retained because of significant loading (Cenfetelli & Bassellier, 2009; Benitez et al., 2017). Table 6 displays the detailed properties of the measurement model.

Construct/dimension/indicator	Mean	S.D.	VIF	Weight	Loading
IT ambidexterity (composite, mode B)	3.613	1.443			
IT exploration (composite, mode B)	3.589	1.361	3.536	0.439***	0.941***
Our firm pursues innovative IT applications	3.860	1.036	3.123	0.301***	0.891***
Our firm experiments with and develops unique IT applications	3.394	0.908	2.356	0.236**	0.887***
Our firm accepts demands that go beyond existing levels of information services	3.477	1.197	3.201	0.261***	0.873***
Our firm regularly searches for and acquires new IT resources (e.g., a new generation of IT architecture, potential IT applications, and critical IT skills)	3.615	1.080	3.100	0.194***	0.852***
Our firm experiments with new IT management practices	3.489	0.984	3.259	0.150^{**}	0.886^{***}
IT exploitation (composite, mode B)	3.636	1.432	3.117	0.583***	0.989***
Our firm frequently refines the existing level of IT components, such as hardware and network resources	3.382	1.105	2.956	0.239***	0.910***
Our firm reuses existing IT skills	3.569	1.763	2.089	0.296***	0.874^{**}
Our firm improves existing IT applications and services	3.863	0.971	3.117	0.195**	0.894***
Our firm continually expands existing IT services for existing clients	3.825	1.104	1.942	0.353***	0.816***
Operational agility (composite, mode B)	3.079	1.391		I	I
We fulfill demands for rapid-response, special requests from our customers whenever such demands arise	2.891	0.826	1.723	0.234**	0.764***
We can easily reconfigure our processes to handle emerging changes	3.102	1.839	1.785	0.349***	0.823***
We can quickly redesign business processes to accommodate fluctuations in demand from the market	3.234	1.241	1.653	0.548***	0.913***
Market complexity (composite, mode B)	3.178	1.611			
In our industry, there is considerable diversity in customer buying habits	3.301	1.268	2.134	0.353***	0.871***
In our industry, there is considerable diversity in product lines	2.937	1.968	2.174	0.316***	0.856***
There have been frequent changes in firm suppliers	3.132	2.015	3.461	0.154	0.873***
Legal regulations have frequently changed the way our firm conducts business	3.331	1.922	3.068	0.323***	0.885***
NPD speed (composite, mode B)	2.594	0.907		•	

Table 6: Measurement model evaluation at first- and second-order levels

NPD speed—survey data	3.236	1.830			
New products/services have been developed and launched faster than a similar product from major competitors	2.813	1.948	2.462	0.339***	0.928***
New products/services have been completed in a shorter time than was considered normal or customary for our industry	3.412	0.902	2.645	0.247*	0.803***
New products/services have been launched on or ahead of the schedule developed at initial product go-ahead	3.114	2.021	3.222	0.246**	0.878***
Top management has been pleased with the time it took us from specifications to full commercialization	3.603	2.684	2.566	0.289**	0.847***
NPD speed—archival data	1.953	1.921			
Firm size: Natural logarithm of the number of full-time employees	4.162	1.051			
Firm age: Natural logarithm of the number of years of the firm's operations	2.568	1.071			
Industry: Manufacturing vs. service	0.450	0.499			
Note: ${}^{*}p < 0.05, {}^{**}p < 0.01, {}^{***}p < 0.001$					

Finally, the saturated model was used to test for the external validity of all composites through a confirmatory composite analysis (Henseler et al., 2014; Benitez-Amado et al., 2017). A confirmatory composite analysis validates the appropriateness of the composite models by equating the empirical correlation matrix with the model-inferred correlation matrix of the saturated model. This analysis also highlights the model misspecifications in terms of a number of constructs or indicators assigned to constructs (Henseler et al., 2014). The results of the confirmatory composite analysis indicate empirical support for this structure of composites at the first- and second-order levels based on an alpha level of 0.05 because all discrepancies are below the 95% quantile of the bootstrap discrepancies. Table 7 shows the details of the confirmatory composite analysis results for saturated models. The aforementioned analysis suggests that the proposed model has good measurement properties and can be processed with a structural assessment for hypothesis testing.

Table 7: Results of the confirmatory composite analysis (saturated model)

D'		First-orde	r level	Second-order level			
Discrepancy	Discrepancy Value HI ₉₅ Control		Conclusion	Value	HI ₉₅	Conclusion	
SRMR	0.026	0.028	Supported	0.015	0.017	Supported	
d _{ULS}	0.319	0.344	Supported	0.006	0.008	Supported	
d _G	0.271	0.289	Supported	0.005	0.010	Supported	

Common method bias

To diminish the common method bias associated with a single means of data collection, we formulated a survey questionnaire following the procedural methods suggested by Podsakoff et al. (2003). Accordingly, the questionnaire was designed to collect data from multiple respondents, and the respondents were assured of the anonymity of the responses. Moreover, we mixed the order of predictor and criterion variables to control for any priming effect and "item-context induced mood state" (Podsakoff et al., 2003, p. 887). Furthermore, our model is operationalized as a composite at the first- and second-order levels. The composite constructs are assumed to be error-free and are incompatible with data containing common method bias (Ronkko & Ylitalo, 2011; Rueda et al., 2017). A composite model is unlikely to suffer from common method bias (Rueda et al., 2017).

In addition, we used a marker variable approach to detect common method bias in our collected data. Following the methodological recommendations of Ronkko & Ylitalo (2011), we chose a single item construct of diversity, i.e., "we respect everyone's different viewpoints" (measured on a 1 to 5 Likert scale in the survey) as marker variables that showed minimal correlation with our key constructs. The regression results for the baseline model without the marker variable were found to be similar to the regression results of the model with the marker variable in terms of beta value and significance, which provides further support that common method variance is not of concern in our data (Ronkko & Ylitalo, 2011). Finally, studies have suggested that the presence of common method bias can undermine the significance of the interaction coefficient (Siemsen, Roth, & Oliveira, 2010). Our results indicate the existence of significant levels of interaction terms in our analyses, suggesting minimal common method bias. Altogether, the threat of common method bias is minimal in this study.

Hypothesis and structural model assessment

The hypothesized relationships were tested by conducting a bootstrap analysis with 5,000 subsamples. The effect size and R² values of these relationships were also evaluated. The baseline model in Table 8 presents all the direct effects on endogenous constructs to test H1, H2, and the direct effect of IT ambidexterity on NPD speed, including all control variables. The empirical analysis suggests that IT ambidexterity enables operational agility (H1) ($\beta = 0.461$, p < 0.001) and that operational agility enhances NPD speed (H2) ($\beta = 0.348$, p < 0.001), providing support for our proposed H1 and H2, respectively.

We performed a mediation analysis to examine whether the indirect effects involved in the proposed models were significant. Following the recommendation of Zhao, Lynch Jr, & Chen (2010), we estimated direct, indirect, and total effects. The empirical analysis reveals that the direct effect in the baseline model between IT ambidexterity and NPD speed was not statistically significant, while the indirect effect was significant ($\beta = 0.189$, p < 0.01), which suggests full mediation of operational agility in the impact of IT ambidexterity on NPD speed (Zhao et al., 2010). Full mediation advocates that the effect of IT ambidexterity on NPD speed is realized through operational agility and therefore supports Hypothesis 3. Table 9 presents a comparison of indirect effects, direct effects, and total effects.

The moderating effects of (1) market complexity and operational agility (on IT ambidexterity) $(\beta = 0.185, p < 0.01)$ and (2) market complexity and operational agility (on NPD speed) $(\beta = 0.121, p < 0.01)$ were significant and positive, supporting Hypotheses 4a and 4b, respectively. To further analyze the effect of these moderation effects on our mediation model, we checked for moderated mediation. Following the methodological approach recommended by Muller, Judd, & Yzerbyt (2005) and Edwards & Lambert (2007), Model 1 tested the moderating effects of market complexity on the direct link between IT ambidexterity and NPD speed, which examines the

overall effect without involving operational agility. Model 2 tested the moderating effects of market complexity on the first-stage mediation link, i.e., the link between IT ambidexterity and operational agility. Model 3 tested the moderating effects of market complexity on both the second-stage mediation link, i.e., the link between operational agility and NPD speed, and the residual direct link. As presented in Table 8, the first-stage mediation link between IT ambidexterity and operational agility (Model 2) is significant ($\beta = 0.185$, p < 0.01), as is the main effect of operational agility on NPD speed in the second-stage mediation link ($\beta = 0.301$, p < 0.001). Together, they indicate that the moderated-mediation effect is not zero (Muller et al., 2005). Following Edwards & Lambert (2007), we then tested the mediation effect under different moderator levels. To do so, market complexity was divided into high (one standard deviation above the mean, n = 129) and low (one standard deviation below the mean, n = 126) groups. The test results reveal that the mediated effect under high market complexity was significant ($\beta = 0.121$, p < 0.01), whereas the mediated effect under low market complexity was not ($\beta = 0.051$, p > 0.10). The findings indicate that the mediated effects in our model depend on the degree of market complexity. Thus, IT ambidexterity affects NPD speed by enhancing operational agility more strongly under conditions of higher market complexity, which lends further support to the moderated-mediation effects.

Moreover, the direct effects of market complexity on NPD speed and operational agility are negative and significant ($\beta = -0.108$, p < 0.05; $\beta = -0.091$, p < 0.10, respectively). These results were expected and support the theoretical arguments that firms face higher uncertainty and information processing in situations of market complexity, thus negatively affecting NPD speed and operational performance. Among control variables, the effect of firm size is positive and significant for all models (p < 0.05), suggesting that the number of employees buttresses firms in gaining NPD speed.

The R^2 values indicate the explanatory power of the model (Chin, 2010; Benitez-Amado et al., 2015). The R^2 values for operational agility and NPD speed range from 0.210 to 0.241 and from 0.258 to 0.320, respectively, which indicates moderate-substantial explanatory power. The f^2 value provides the relative size of each incremental link introduced in the model. f^2 values of 0.02, 0.15, and 0.35 indicate a weak, medium, or large effect size, respectively (Leal-Rodríguez, Roldán, Ariza-Montes, & Leal-Millán, 2014; Braojos-Gomez et al., 2015). f^2 values in our hypothesized relationships ranged from 0.114 to 0.271, indicating medium to strong effect sizes. Table 8 provides an overview of effect sizes for all relationships.

Finally, we conducted a confirmatory composite analysis to evaluate the goodness-of-model fit for our structural model. The goodness-of-fit model was tested by evaluating the unweighted least squares (ULS) discrepancy (d_{ULS}) and the geodesic discrepancy (d_G) between the empirical correlation matrix and the model-implied correlation matrix of the estimated model (Henseler, 2015; Benitez-Amado et al., 2017) and through a standardized root-mean-squared residual (SRMR) value that should be lower than 0.080. The SRMR value of the proposed model was 0.011, and all discrepancies were below the 95% quantile, suggesting that the proposed structural model fits the data well. Table 10 presents the correlation matrix.

Dependent variable - Inc	→ lependent variable	Baseline model	Model 1	Model 2	Model 3
IT ambidexterity \rightarrow	Operational agility	0.461 ^{***} (8.903) [0.323, 0.558]		0.441*** (6.812) [0.277, 0.593]	0.414*** (5.889) [0.262, 0.573]
Operational agility \rightarrow	NPD speed	0.348 ^{***} (5.362) [0.185, 0.478]			0.301 ^{***} (4.758) [0.193, 0.469]
IT ambidexterity \rightarrow	NPD speed	0.095 (0.661) [0.010, 0.099]	0.103 (0.784) [0.021, 0.141]		0.101 (0.780) [0.024, 0.137]

Table 8: Structural model evaluation results

Market complexity \rightarrow NPD speed			-0 (-1 [-0.20).108 [*] 1.139))1, 0.047]			-0.1 (-1. [-0.233	103 [*] 125) 5, 0.093]	
IT ambidexterity x market complexity → NPD speed			0 (0 [0.06	.110 [†]).977) 3, 0.193]			0.0 (0.9 [0.068	98† 966) , 0.181]	
Market complexity → Operational agility					-0.0 (-0.9 [-1.112)91 [†] 906) , 0.055]			
IT ambidexterity x market complexity → Operational agility					0.185** (2.327) [0.019, 0.344]				
Operational agility x market complexity → NPD speed							0.1 (2.4 [0.011]	21** 493) , 0.279]	
Firm size (control variable) → NPD speed	0.12 (1.13 [0.087, 0	4* 62) 0.192]	0 (1 [0.08	.132* .217) 0, 0.203]			0.1 (1.1 [0.089,	25* 37) 0.195]	
Firm age (control variable) \rightarrow NPD speed	0.08 (0.41 [-0.130, -	89 1) 0.145]	0.086 (0.440) [-0.131, -0.142]		9 0.086 1) (0.440) 0.145] [-0.131, -0.142]			0.0 (0.4 [-0.130,	089 -11) -0.145]
Industry (control variable) \rightarrow NPD speed	-0.05 (-0.18	59 37)	-0.051 (-0.189) [-0.186, 0.082]				-0. (-0.	060 183)	
	[-0.188,	0.041]	[-0.18	86, 0.082]			[-0.187	, 0.041]	
Endogenous variable	[-0.188, 0	0.041] Adj. R ²	[-0.18 R ²	36, 0.082] Adj. R ²	R ²	Adj. R ²	[-0.187] R ²	, 0.041] Adj. R ²	
Endogenous variable Operational agility	[-0.188, 0 R ² 0.213	0.041] Adj. R ² 0.206	[-0.18 R²	Adj. R ²	R ² 0.245	Adj. R² 0.237	[-0.187] R ² 0.213	, 0.041] Adj. R ² 0.206	
Endogenous variable Operational agility NPD speed	[-0.188, 0 R² 0.213 0.262	0.041] Adj. R ² 0.206 0.253	[-0.18 R² - 0.275	Adj. R ² - 0.263	R ² 0.245	Adj. R ² 0.237	[-0.187, R² 0.213 0.339	, 0.041] Adj. R ² 0.206 0.321	
Endogenous variable Operational agility NPD speed SRMR value	[-0.188, 0 R ² 0.213 0.262 0.01	0.041] Adj. R ² 0.206 0.253 1	[-0.18 R ² - 0.275	Adj. R ² - 0.263 0.024	R ² 0.245 - 0.0	Adj. R ² 0.237 - 014	[-0.187, R² 0.213 0.339 0.0	, 0.041] Adj. R ² 0.206 0.321 021	
Endogenous variable Operational agility NPD speed SRMR value SRMR HI95	[-0.188, 0 R ² 0.213 0.262 0.01 0.03	0.041] Adj. R² 0.206 0.253 1 00	[-0.18 R ² - 0.275 0 0	Adj. Adj. R ² - 0.263 0.024 0.031	R ² 0.245 - 0.0 0.0	Adj. R ² 0.237 - 014 021	[-0.187, R ² 0.213 0.339 0.0 0.0	, 0.041] Adj. R ² 0.206 0.321 021 026	
Endogenous variable Operational agility NPD speed SRMR value SRMR HI95 duls value	[-0.188, 0 R ² 0.213 0.262 0.01 0.03 0.00	0.041] Adj. R ² 0.206 0.253 1 00 03	[-0.18 R ² - 0.275 0 0 0 0 0 0 0 0 0 0 0 0 0	Adj. R ² - 0.263 0.024 0.031 0.017	R ² 0.245 - 0.0 0.0 0.0	Adj. R ² 0.237 - 014 021	[-0.187, R ² 0.213 0.339 0.0 0.0 0.0	, 0.041] Adj. R ² 0.206 0.321 021 026 024	
Endogenous variable Operational agility NPD speed SRMR value SRMR HI95 duLs value duLs HI95	[-0.188, 0 R ² 0.213 0.262 0.01 0.03 0.00 0.01	0.041] Adj. R ² 0.206 0.253 1 00 03 7	[-0.18 R ² - 0.275 0 0 0 0 0 0 0 0 0 0 0 0 0	36, 0.082] Adj. R ² - 0.263 0.024 0.031 0.017 0.021	R ² 0.245 - 0.0 0.0 0.0 0.0	Adj. R ² 0.237 - 014 021 011 019	[-0.187, R ² 0.213 0.339 0.0 0.0 0.0 0.0	, 0.041] Adj. R ² 0.206 0.321 021 026 024 030	
Endogenous variable Operational agility NPD speed SRMR value SRMR HI95 duLs value duLs HI95 dG value	[-0.188, 0 R ² 0.213 0.262 0.01 0.03 0.00 0.01 0.00	0.041] Adj. R ² 0.206 0.253 1 00 03 7 01	[-0.18 R ² 0.275 00 00 00 00 00 00 00 00 00 0	36, 0.082] Adj. R ² 0.263 0.024 0.031 0.017 0.021 0.002	R ² 0.245 - 0.0 0.0 0.0 0.0 0.0	Adj. R ² 0.237 - 014 011 011 019 005 000	[-0.187, R ² 0.213 0.339 0.0 0.0 0.0 0.0 0.0 0.0 0.0	, 0.041] Adj. R ² 0.206 0.321 021 026 024 030 006 010	
Endogenous variable Operational agility NPD speed SRMR value GULS Value GULS HI95 GG value GG Value GG HI95	[-0.188, 0 R ² 0.213 0.262 0.01 0.03 0.00 0.01 0.00 0.00	0.041] Adj. R ² 0.206 0.253 1 00 03 7 01 06	[-0.18 R ² 0.275 00 00 00 00 00 00 00 00 00 0	Adj. R ² - 0.263 0.024 0.031 0.017 0.021 0.002 0.007	R ² 0.245 - 0.0 0.0 0.0 0.0 0.0 0.0	Adj. R ² 0.237 - 014 021 019 005 008	[-0.187, R ² 0.213 0.339 0.0 0.0 0.0 0.0 0.0 0.0 0.0	, 0.041] Adj. R ² 0.206 0.321 026 024 030 006 010	
Endogenous variable Operational agility NPD speed SRMR value SRMR HI95 duLs value duLs HI95 dG value dG HI95 f ² IT ambidatority a Operational agility	[-0.188, 0 R ² 0.213 0.262 0.01 0.03 0.00 0.00 0.00 0.00	0.041] Adj. R ² 0.206 0.253 1 00 03 7 01 06	[-0.18 R ² 0.275 00 00 00 00 00 00 00 00 00 0	Adj. Adj. R ² 0.263 0.024 0.031 0.017 0.021 0.002	R ² 0.245 - 0.0 0.0 0.0 0.0 0.0 0.0	Adj. R ² 0.237 - 014 011 011 019 005 008	[-0.187, R ² 0.213 0.339 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.	, 0.041] Adj. R ² 0.206 0.321 021 026 024 030 006 010 0261	
Endogenous variableOperational agilityNPD speedSRMR valueduts valueduts valueduts HI95dG valuedG HI95f²IT ambidexterity \rightarrow Operational agilityOperational agility	[-0.188, 0 R ² 0.213 0.262 0.01 0.03 0.00 0.	0.041] Adj. R ² 0.206 0.253 1 00 03 7 01 06 (1 1 1	[-0.18 R ² 0.275 00 00 00 00 00 00 00 00 00 0	Adj. R ² - 0.263 0.024 0.031 0.017 0.002 0.007	R ² 0.245 - 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0	Adj. R ² 0.237 - 014 021 011 019 005 008 268	[-0.187, R ² 0.213 0.339 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.	, 0.041] Adj. R ² 0.206 0.321 026 024 030 006 010 261 182	
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Endogenous variableEndogenous variableOperational agilityNPD speedSRMR valueduts valueduts valuedg valuedG valuedG valuedG tablesf²IT ambidexterity \rightarrow Operational agilityOperational agility \rightarrow NPD speedIT ambidexterity \rightarrow Operational agility	[-0.188, 0 R ² 0.213 0.262 0.01 0.03 0.00 0.01 0.00 0.	0.041] Adj. R ² 0.206 0.253 1 00 03 7 01 06 1 1 66	[-0.18 R ² 0.275 0.275 0 0 0 0 0 0 0 0 0 0 0 0 0	36, 0.082] Adj. R ² 0.263 0.024 0.031 0.017 0.021 0.002 0.007	R ² 0.245 - 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0	Adj. R ² 0.237 - 014 021 019 005 008 268 268	[-0.187, R ² 0.213 0.339 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.	, 0.041] Adj. R ² 0.206 0.321 021 026 024 030 006 010 261 182 045 103 078	

Operational agility x market complexity \rightarrow NPD speed				0.114		
Firm size \rightarrow NPD speed	0.086	0.088		0.084		
Firm age \rightarrow NPD speed	0.012	0.065		0.014		
Industry \rightarrow NPD speed	0.003	0.003		0.004		

Note: t-values in parentheses. Bootstrapping 95% confidence interval bias corrected in square brackets (based on n = 4,999 subsamples). $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ [based on n = 5,000, one-tailed test]

Table 9: Results of the mediation analysis

Relationship	Indirect effect	Direct effect	Total effect
IT ambidexterity → NPD speed Baseline model	0.189** (2.516) [0.058, 0.274]	0.095 (0.661) [0.010, 0.099]	0.270^{*} (1.593) [0.105, 0.329]
Note: t-values in parentheses. Bootstrapping 95% confi 4,999 subsamples). * $p < 0.05$, ** $p < 0.01$ [based on n = 5	idence interval bias co 5,000, one-tailed test]	prrected in square brac	ckets (based on n =

Table 10: Correlation matrix							
	1	2	3	4	5	6	7
1. IT ambidexterity	1.000						
2. Operational agility	0.462**	1.000					
3. Market complexity	0.264**	0.350**	1.000				
4. NPD speed	0.361**	0.393**	0.314**	1.000			
5. Ln firm size	0.230**	0.152**	0.378**	0.187**	1.000		
6. Ln firm age	0.049†	-0.046	0.058	0.023†	0.379**	1.000	
7. Industry	0.073	0.150†	0.213*	-0.091	0.056	0.040	1.000
Note: [†] p < 0.10, [*] p < 0.05, ^{**} p < 0.01	1						

Robustness checks

We further verified our research findings by considering an alternate measure of the combination method for the IT ambidexterity construct in our study. Following prior studies that operationalize ambidexterity construct as multiplicative interaction of exploitation and exploration (i.e., Jansen et al., 2006, Lee et al., 2015), we repeated the test of our hypotheses by measuring IT ambidexterity as multiplicative interaction of IT exploitation and IT exploration and found consistent results. Hypotheses 1 and 2 were supported ($\beta = 0.389$, p < 0.001 and $\beta = 0.227$, p < 0.001, respectively), Hypothesis 3 for mediation was supported ($\beta = 0.041$, p > 0.10 and $\beta = 0.174$, p < 0.01 for direct and indirect effects, respectively), and the results upheld Hypotheses 4a and 4b ($\beta = 0.179$, p < 0.01

and $\beta = 0.113$, p < 0.01, respectively). The overall findings of the multiplicative measurement model replicated the hypothesized results of the composite measurement model of ambidexterity, consistent with prior studies that tested alternative ambidexterity measures (e.g., Jansen, Tempelaar, Van den Bosch, & Volberda, 2009). Overall, our robustness checks provide support for our hypothesized model and validate our results.

DISCUSSION AND CONCLUSIONS

Implications and key contributions to IS research

Despite the important influence of IT capabilities on NPD speed, empirical evidence for the underlying mechanisms of this influence is scarce. To address this gap, this study has explored the role of operational agility in the relationship between firms' IT capabilities and NPD speed. Our findings suggest that IT ambidexterity enhances NPD speed by facilitating operational agility, and this effect is more pronounced in contexts with higher market complexity.

A key contribution of our research lies in its theoretical extensions of the extant IT-enabled NPD speed-creation literature by providing an advanced nomological model of the relationships among IT ambidexterity, operational agility, NPD speed, and market complexity. The theoretical argumentation of our model applies the emerging perspective of ambidexterity in IS research to achieve a comprehensive understanding of how the presence of superior IT capability within a firm interacts with operational capabilities to stimulate rapid NPD speed. The moderated-mediation analysis provides a better understanding of how the complex mediating relationships are influenced by moderators (Muller et al., 2005; Edwards & Lambert, 2007). Consequently, the empirical evidence permits a more nuanced understanding by revealing that market complexity provides an important boundary condition for the effectiveness of IT ambidexterity in enabling enhanced NPD

speed. Overall, our moderated-mediation model contributes by considering both how and when IT ambidexterity enhances NPD speed as opposed to fragmented insights from focusing on only one of these questions. Such a joint analysis (moderated-mediation models) presents an interesting and relevant insight for academia by providing a complete perspective on key constructs, i.e., IT ambidexterity. Specifically, management practitioners can learn from this study because decision-makers must consider both the internal aspects of their firms and market conditions collectively.

Another key contribution of this study lies in the theoretical extensions of IT ambidexterity capability. Today's fast-paced industries are characterized by frequent changes in product/process technologies and increased competitive intensity. To flourish or even survive in these environments, firms need to explore and exploit their IT resources simultaneously. Despite its importance, IT ambidexterity has been proposed and investigated only very recently by Lee et al. (2015); therefore, our understanding in the field of IS is very limited. While the critical concern in the IS literature is how to derive the business value of IT, the flexible use of various IT-related constructs (i.e., IT spending, IT investment, IT artifacts) that can be easily imitated by competitors may have hindered a consistent understanding of the strategic role of IT capabilities. To address these issues, this study theoretically developed and empirically tested the business value of IT ambidexterity in an NPD context. By conceptualizing the nature of IT ambidexterity, operationalizing its key dimensions, and showing its impact on NPD speed, this study has implications for understanding how NPD work units can leverage IT capabilities to enhance NPD speed. The resulting theory and empirical evidence can yield further insights into conceptualizing, operationalizing, and understanding the business value of IT ambidexterity.

Another open debate in the literature is whether IT-related constructs influence competitive advantage directly or indirectly (Pavlou & El Sawy, 2006). Taking the indirect view, we propose a

research model to delineate the mechanisms by which IT ambidexterity helps build a competitive advantage in NPD under market complexity. We draw on the IT-enabled organizational capability perspective to theoretically explain and empirically demonstrate how IT ambidexterity enacts operational agility to influence NPD speed. Our findings supplement our theoretical arguments that enhanced IT capability—IT ambidexterity—augments the reach and richness of a firm's operations, helping the firm develop the potential to sense change and swiftly adapt its operational processes. In light of this theory, IT ambidexterity can be considered to provide a digitized platform facilitating the building of operational capabilities, such as operational agility, which enables competitive maneuvers, such as NPD speed. Whereas the literature on IT capability has primarily focused on IT units, this study reveals that the implications of IT capability can arise outside the IT unit with capability-building initiatives. Consequently, this study implies that researchers who only study IS strategies at the IT-unit level may be overlooking some strategic effects of IT.

This research contributes to transdisciplinary literature streams (IS and operations management) by empirically investigating the synergistic value realized when IT and operational capabilities are linked. The respective literature on IT ambidexterity and operational agility has evolved separately; this study seeks to close this gap by exhibiting the interplay between IT ambidexterity and operational agility working towards a consistent goal. Beyond viewing IT ambidexterity as a distinct capability in its own right, we contribute a demonstration of IT ambidexterity as a supporting capability for firm operations, thus indirectly impacting NPD success. The resulting theoretical arguments and empirical results can motivate future research tapping into the business value of linking IS and operational (IT integrated operations) strategies. The implications are evident in many existing businesses, such as Amazon solving plant-floor optimization problems with smart warehouse robots. Moreover, this research can be interpreted as an incremental

extension of the study of Acur et al. (2010). Acur and her colleagues examined the effect of two distinctive IT capabilities—technological alignment and technological competence—on NPD speed and reported a negative and a positive relationship, respectively (Acur et al., 2010). Our research extends and refines their work by offering an ambidextrous approach to such distinctive IT capabilities and highlights the notion that key IT capabilities should be channeled through the operational processes of the firm to realize NPD speed. For instance, HiETA Technologies uses 3D printing to reduce the turnaround times for product prototypes from weeks to hours.

Finally, our findings contribute to the limited research on the importance of external influences when implementing IT-enabled competitive maneuvers. While the majority of studies focusing on IT-enabled organizational capabilities examine their impact on performance measures, few have considered the role of exogenous factors (Ravishankar, Pan, & Leidner, 2011; Benitez & Walczuch, 2012; Tan et al., 2017). Our study contributes to this literature by demonstrating the key role played by market complexity in realizing the business value of IT-enabled operational mechanisms. Our results for moderated mediation suggest that market complexity acts as a boundary condition for operational agility to mediate the relationship between IT ambidexterity and NPD speed. These findings can benefit IS theory and practice by resuscitating the role of exogenous factors, which are usually undervalued.

Limitations and future research directions

This research has the following limitations. First, the results of our research are based on crosssectional data, and the study's data have limitations of a perceptual nature (Bowen & Wiersema, 1999). Longitudinal or experimental research may provide a better understanding of the nomological relationships among research variables. Second, our sample can be generalized only to high-tech SMEs in the UK market. Although we controlled for the industry, findings may be

different for large firms and may vary by industry. Moreover, we have not explored whether the proposed theoretical model is supported in high-tech SMEs in other markets (e.g., Asia, Europe, & Latin America). Third, we examined IT ambidexterity at the firm level. We acknowledge that IT ambidexterity may occur at the level of individuals or departments; thus, our firm-level observations might present a relatively high-level representation of the nature and impact of this IT capability. Despite the fact that our key respondents were from top management, suggesting the validity of our results about the firms' use of IT, future research should also study IT ambidexterity at the level of individuals or departments. Finally, although our theoretical model is logical and our measurement and the structural model analysis presented a good model fit, we proposed a model that could be extended by investigating additional or alternative mediators and moderators. For example, Lee, Xu, Kuilboer, & Ashrafi (2016) suggest comparative settings of manufacturing and service industries to evaluate the influence of IT capabilities on agility. Similarly, Fang (2008) discusses the role of customer participation in delivering accelerated NPD speed. We hope further research will utilize, refine, and extend the findings of this study to contribute to a better theory of IT-enabled organizational capability for enhancing NPD speed.

Implications for managers

Our research findings provide three key lessons for IS executives. First, our findings suggest that IT ambidexterity plays a fundamental direct (on operational capabilities) and indirect role (on performance measures) in an NPD context. This lesson highlights the importance of developing a balanced approach in IT management practices, which is to continually refine and extend existing IT resources and IT practices for current market needs and, at the same time, explore better solutions and develop innovative IT solutions for future markets to achieve competitive outcomes. Second, our results indicate that the impact of IT ambidexterity on NPD speed is realized through

a mediating effect of operational agility. Thus, managers should strive to guarantee that IT ambidexterity capability is channeled through the key operational processes of the firm. For instance, Xiros Limited, a UK-based high-tech SME, competes to rapidly turn innovative ideas into fully developed commercial products. Their operational strategy focuses on FASTRAX service (a stage-gate system for customization and speed), converting concepts into complete solutions through a rigorous technology-supported project development process. Third, our findings highlight the imperative role played by market conditions in realizing the optimum benefits of IT capability. In particular, our results suggest that firms in complex markets should focus their efforts on the development and integration of their IT capabilities with operational processes to maximize NPD speed.

REFERENCES

Acur, N., Kandemir, D., Weerd-Nederhof, D., Petra, C., & Song, M. (2010). Exploring the impact of technological competence development on speed and NPD program performance. Journal of Product Innovation Management, 27(6), 915-929.

Attaran, M. (2004). Exploring the relationship between information technology and business process reengineering. Information & Management, 41(5), 585-596.

Barczak, G., Hultink, E. J., & Sultan, F. (2008). Antecedents and consequences of information technology usage in NPD: A comparison of Dutch and US companies. Journal of Product Innovation Management, 25(6), 620-631.

Barczak, G., Sultan, F., & Hultink, E. J. (2007). Determinants of IT usage and new product performance. Journal of Product Innovation Management, 24(6), 600-613.

Benitez, J., Castillo, A., Llorens, J., & Braojos, J. (2017). IT-enabled knowledge ambidexterity and innovation performance in small US firms: The moderator role of social media capability. Information & Management, 55(1), 131-143.

Benitez, J., Chen, Y., Teo, T., & Ajamieh, A. (2018a). Evolution of the impact of e-business technology on operational competence and firm profitability: A panel data investigation. Information & Management, 55(1), 120-130.

Benitez, J., Llorens, J., & Braojos, J. (2018b). How information technology influences opportunity exploration and exploitation firm's capabilities. Information & Management, 55(4), 508-523.

Benitez, J., Ray, G., & Henseler, J. (2018c). Impact of information technology infrastructure flexibility on mergers and acquisitions. MIS Quarterly, 42(1), 25-43.

Benitez, J., & Walczuch, R. (2012). Information technology, the organizational capability of proactive corporate environmental strategy and firm performance: A resource-based analysis. European Journal of Information Systems, 21(6), 664-679.

Benitez-Amado, J., Henseler, J., & Castillo, A. (2017). Development and update of guidelines to perform and report partial least squares path modeling in information systems research. In the proceedings of 21st Pacific Asia Conference on Information Systems. Langkawi Malaysia, 1-15.

Benitez-Amado, J., Llorens-Montes, F. J., & Fernandez-Perez, V. (2015). IT impact on talent management and operational environmental sustainability. Information Technology and Management, 16(3), 207-220.

Benner, M. J., & Tushman, M. L. (2003). Exploitation, exploration, and process management: The productivity dilemma revisited. Academy of Management Review, 28(2), 238-256.

Bollen, K., & Diamantopoulos, A. (2017). In defense of causal-formative indicators: A minority report. Psychological Methods, 22(3), 581-596.

Bowen, H. P., & Wiersema, M. F. (1999). Matching method to paradigm in strategy research: Limitations of cross-sectional analysis and some methodological alternatives. Strategic Management Journal, 20(7), 625-636.

Braojos, J., Benitez, J., & Llorens, J. (2018). How do social commerce-IT capabilities influence firm performance? Theory and empirical evidence. Information & Management, (in press), 1-17.

Braojos-Gomez, J., Benitez-Amado, J., & Llorens-Montes, F. J. (2015). How do small firms learn to develop a social media competence? International Journal of Information Management, 35(4), 443-458.

Cenfetelli, R. T., Bassellier, G. (2009). Interpretation of formative measurement in information systems research. MIS Quarterly, 33(4), 689-707.

Chandrasekaran, A., Linderman, K., & Schroeder, R. (2012). Antecedents to ambidexterity competency in high technology organizations. Journal of Operations Management, 30(1), 134-151.

Chen, J., Damanpour, F. and Reilly, R.R., 2010. Understanding antecedents of new product development speed: A meta-analysis. Journal of Operations Management, 28(1), 17-33.

Chen, J., Reilly, R., & Lynn, G. (2005). The impacts of speed-to-market on new product success: The moderating effects of uncertainty. IEEE Transactions on Engineering Management, 52(2), 199-212.

Chen, Y., Wang, Y., Nevo, S., Jin, J., Wang, L., & Chow, W. S. (2014). IT capability and organizational performance: The roles of business process agility and environmental factors. European Journal of Information Systems, 23(3), 326-342.

Chin, W. W. (2010). How to write up and report PLS analyses. In W. C. V. Esposito, J. Henseler, H. Wang (Eds.), Handbook of partial least squares: Concepts, methods and applications. Berlin, Germany: Springer, 655-690.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). USA: Erlbaum, Hillsdale.

Cotteleer, M. J., & Bendoly, E. (2006). Order lead-time improvement following enterprise information technology implementation: An empirical study. MIS Quarterly, 30(3), 643-660.

D'Aveni, R. A., Dagnino, G. B., & Smith, K. G. (2010). The age of temporary advantage. Strategic Management Journal, 31(13), 1371-1385.

Department for Business Innovation Skills (2011). Small and medium sized enterprise statistics for the UK and regions, accessed January 19, 2017, available at https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/32514/bpe_2010_-_statistical_release.pdf.

Dess, G. G., & Beard, D. W. (1984). Dimensions of organizational task environments. Administrative Science Quarterly, 29(1), 52-73.

Devaraj, S., & Kohli, R. (2003). Performance impacts of information technology: Is actual usage the missing link? Management Science, 49(3), 273-289.

Dijkstra, T., & Henseler, J. (2015). Consistent partial least squares path modeling. MIS Quarterly, 39(2), 297-316.

Dutta, S., Lanvin, B., & Wunsch, S., (2018). Energizing the World with innovation, Global Innovation Index report, accessed May 5, 2018, available at https://www.globalinnovationindex.org/userfiles/file/reportpdf/GII%202018%20Full%20print.W EB.pdf.Edwards, J. R., & Lambert, L. S. (2007). Methods for integrating moderation and mediation: A general analytical framework using moderated path analysis. Psychological Methods, 12(1), 1-22.

Fang, E. (2008). Customer participation and the trade-off between new product innovativeness and speed to market. Journal of Marketing, 72(4), 90-104.

Feng, T., Sun, L., Zhu, C., & Sohal, A. S. (2012). Customer orientation for decreasing time-tomarket of new products: IT implementation as a complementary asset. Industrial Marketing Management, 41(6), 929-939.

Galbraith. J. (1974). Organization design: An information processing view. Interfaces, 4(3), 28-36.

Garcia, R., Calantone, R. & Levine, R. (2003). The role of knowledge in resource allocation to exploration versus exploitation in technologically oriented organizations. Decision Sciences, 34(2), 323-349.

George, K., Ramaswamy, S., & Rassey, L. (2014). Next-shoring: A CEO's guide. McKinsey Quarterly, 1, 26-39.

Gibson, C. B., & Birkinshaw, J. (2004). The antecedents, consequences, and mediating role of organizational ambidexterity. Academy of Management Journal, 47(2), 209-226.

Gregory, R. W., Keil, M., Muntermann, J., & Mähring, M. (2015). Paradoxes and the nature of ambidexterity in IT transformation programs. Information Systems Research, 26(1), 57-80.

Gupta, A. K., Smith, K. G., & Shalley, C. E. (2006). The interplay between exploration and exploitation. Academy of Management Journal, 49(4), 693-706.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. Journal of the Academy of Marketing Science, 40(3), 414-433.

Harter, D., Krishnan, M., & Slaughter, S. (2000). Effects of process maturity on quality, cycle time, and effort in software product development. Management Science, 46(4), 451-466.

He, Z.-L., & Wong, P.-K. (2004). Exploration vs. exploitation: An empirical test of the ambidexterity hypothesis. Organization Science, 15(4), 481-494.

Henseler, J. (2015). Is the whole more than the sum of its parts? On the interplay of marketing and design research. University of Twente, Enschede, The Netherlands,1-10.

Henseler, J. (2017). Bridging design and behavioral research with variance-based structural equation modeling. Journal of Advertising, 46(1), 178-192.

Henseler, J., & Dijkstra, T. (2015). ADANCO 2.0.1 Professional for Windows. Composite Modeling, Kleve, Germany, http://www.composite-modeling.com.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. et al. (2014). Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013). Organizational Research Methods, 17(2), 182-209.

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. Industrial Management & Data Systems, 116(1), 2-20.

Holgersson, M. (2013). Patent management in entrepreneurial SMEs: A literature review and an empirical study of innovation appropriation, patent propensity, and motives. R&D Management, 43(1), 21-36.

Huang, P.-Y., Ouyang, T. H., Pan, S. L., & Chou, T.-C. (2012). The role of IT in achieving operational agility: A case study of Haier, China. International Journal of Information Management, 32(3), 294-298.

Im, G., Rai, A. & Lambert, L.S. (2019). Governance and resource-sharing ambidexterity for generating relationship benefits in supply chain collaborations. Decision Sciences. forthcoming.

Jansen, J. J., Tempelaar, M. P., Van den Bosch, F. A., & Volberda, H. W. (2009). Structural differentiation and ambidexterity: The mediating role of integration mechanisms. Organization Science, 20(4), 797-811.

Jansen, J. J., Van Den Bosch, F. A., & Volberda, H. W. (2006). Exploratory innovation, exploitative innovation, and performance: Effects of organizational antecedents and environmental moderators. Management Science, 52(11), 1661-1674.

Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. Journal of Consumer Research, 30(2), 199-218.

Kessler, E., & Chakrabarti, A. (1999). Speeding up the pace of new product development. Journal of Product Innovation Management, 16(3), 231-247.

Koufteros, X.A., Rawski, G.E. & Rupak, R. (2010). Organizational integration for product development: The effects on glitches, on-time execution of engineering change orders, and market success. Decision Sciences, 41(1), 49-80.

Kumar, A., & Motwani, J. (1995). A methodology for assessing time-based competitive advantage of manufacturing firms. International Journal of Operations & Production Management, 15(2), 36-53.

Leal-Rodríguez, A. L., Roldán, J. L., Ariza-Montes, J. A., & Leal-Millán, A. (2014). From potential absorptive capacity to innovation outcomes in project teams: The conditional mediating role of the realized absorptive capacity in a relational learning context. International Journal of Project Management, 32(6), 894-907.

LeBreton, J., & Senter, J. (2008). Answers to 20 questions about interrater reliability and interrater agreement. Organizational Research Methods, 11(4), 815-852.

Lee, H. (2004). The triple-A supply chain. Harvard Business Review, 82(10), 102-113.

Lee, O.-K., Sambamurthy, V., Lim, K. H., & Wei, K. K. (2015). How does IT ambidexterity impact organizational agility? Information Systems Research, 26(2), 398-417.

Lee, O.-K. D., Xu, P., Kuilboer, J.-P., & Ashrafi, N. (2016). Idiosyncratic Values of IT-enabled Agility at the Operation and Strategic Levels. Communications of the Association for Information Systems, 39(1), 13.

Levinthal, D. A., & March, J. G. (1993). The myopia of learning. Strategic Management Journal, 14(S2), 95-112.

Lu, Y., & Ramamurthy, K. (2011). Understanding the link between information technology capability and organizational agility: An empirical examination. MIS Quarterly, 35(4), 931-954.

March, J. G. (1991). Exploration and exploitation in organizational learning. Organization Science, 2(1), 71-87.

McNally, R. C., Akdeniz, M. B., & Calantone, R. J. (2011). New product development processes and new product profitability: Exploring the mediating role of speed to market and product quality. Journal of Product Innovation Management, 28(1), 63-77.

Mithas, S., Ramasubbu, N., & Sambamurthy, V. (2011). How information management capability influences firm performance. MIS Quarterly, 35(1), 237-256.

Mithas, S., & Rust, R. T. (2016). How information technology strategy and investments influence firm performance: Conjectures and empirical evidence. MIS Quarterly, 40(1), 223-245.

Muller, D., Judd, C. M., & Yzerbyt, V. Y. (2005). When moderation is mediated and mediation is moderated. Journal of Personality and Social Psychology, 89(6), 852.

Nambisan, S. (2013). Information technology and product/service innovation: A brief assessment and some suggestions for future research. Journal of the Association for Information Systems, 14(4), 215-226.

Oke, A., Burke, G., & Myers, A. (2007). Innovation types and performance in growing UK SMEs. International Journal of Operations & Production Management, 27(7), 735-753.

Overby, E., Bharadwaj, A., & Sambamurthy, V. (2006). Enterprise agility and the enabling role of information technology. European Journal of Information Systems, 15(2), 120-131.

Pavlou, P. A., & El Sawy, O. A. (2006). From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development. Information Systems Research, 17(3), 198-227.

Petter, S., Straub, D., & Rai, A. (2007). Specifying formative constructs in information systems research. MIS Quarterly, 31(4), 623-656.

Pfeffer, J., & Salancik, G. (1978). The external control of organizations: A resource dependence perspective. New York: Harper & Row.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. Journal of Management, 12(4), 531-544.

Rai, A., Patnayakuni, R., & Seth, N. (2006). Firm performance impacts of digitally enabled supply chain integration capabilities. MIS Quarterly, 30(2), 225-246.

Raisch, S., Birkinshaw, J., Probst, G., & Tushman, M. L. (2009). Organizational ambidexterity: Balancing exploitation and exploration for sustained performance. Organization Science, 20(4), 685-695.

Ravishankar, M., Pan, S. L., & Leidner, D. E. (2011). Examining the strategic alignment and implementation success of a KMS: A subculture-based multilevel analysis. Information Systems Research, 22(1), 39-59.

Ronkko, M., & Ylitalo, J. (2011). PLS marker variable approach to diagnosing and controlling for method variance. Proceedings of the 32nd International Conference on Information Systems. Shanghai, China, 1-16.

Rueda, L., Benitez, J., & Braojos, J. (2017). From traditional education technologies to student satisfaction in Management education: A theory of the role of social media applications. Information & Management, 54(8), 1059-1071.

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. MIS Quarterly, 27(2), 237-263.

Siemsen, E., Roth, A., & Oliveira, P. (2010). Common method bias in regression models with linear, quadratic, and interaction effects. Organizational Research Methods, 13(3), 456-476.

Siggelkow, N., & Rivkin, J. (2005). Speed and search: Designing organizations for turbulence and complexity. Organization Science, 16(2), 101-122.

Stoel, M. D., & Muhanna, W. A. (2009). IT capabilities and firm performance: A contingency analysis of the role of industry and IT capability type. Information & Management, 46(3), 181-189.

Tallon, P. P., & Pinsonneault, A. (2011). Competing perspectives on the link between strategic information technology alignment and organizational agility: insights from a mediation model. MIS Quarterly, 35 (2), 463-486.

Tan, F. T., Tan, B., Wang, W., & Sedera, D. (2017). IT-enabled operational agility: An interdependencies perspective. Information & Management, 54(3), 292-303.

Thatcher, J. B., & Perrewe, P. L. (2002). An empirical examination of individual traits as antecedents to computer anxiety and computer self-efficacy. MIS Quarterly, 26(4), 381-396.

Tippins, M. J., & Sohi, R. S. (2003). IT competency and firm performance: Is organizational learning a missing link? Strategic Management Journal, 24(8), 745-761.

Tsai, K.-H., & Yang, S.-Y. (2013). Firm innovativeness and business performance: The joint moderating effects of market turbulence and competition. Industrial Marketing Management, 42(8), 1279-1294.

Vesey, J. T. (1991). The new competitors: they think in terms of 'speed-to-market'. The Executive, 5(2), 23-33.

Yusuf, Y. Y., Sarhadi, M., & Gunasekaran, A. (1999). Agile manufacturing: The drivers, concepts and attributes. International Journal of Production Economics, 62(1), 33-43.

Zaheer, A., & Zaheer, S. (1997). Catching the wave: Alertness, responsiveness, and market influence in global electronic networks. Management Science, 43(11), 1493-1509.

Zhao, X., Lynch Jr, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. Journal of Consumer Research, 37(2), 197-206.