IT-enabled knowledge ambidexterity and innovation performance in small U.S. small firms: The moderator role of social media capability

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IT-enabled knowledge ambidexterity and innovation performance in small U.S. firms: The moderator role of social media capability

Highlights

- A theory of business value of IT
- Empirical study on a sample composed of 100 small firms
- IT infrastructure enables firms to explore and exploit knowledge to innovate
- Social media play a role of complementary IT capability on this equation

Abstract

This study examines the impact of information technology (IT)-enabled knowledge ambidexterity on innovation performance, and the potential moderator role of social media capability on a sample composed of 100 small U.S. firms. The empirical analysis suggests that IT infrastructure enables the firm to explore new knowledge and exploit existing/new knowledge to innovate more and better. We also find that social media capability has a positive moderator role in this equation: IT infrastructure and social media capabilities work together to enable knowledge ambidexterity.

Keywords*:* IT infrastructure, knowledge exploration and exploitation, social media capability, innovation performance.

1. Introduction

In the contemporary business environment, the firm's capture, analysis, and dissemination of knowledge are knowledge management activities that have the potential to explain a significant portion of variation in firm performance (Alavi & Leidner 2001; Sher & Lee 2004). For instance, Capgemini (a European consulting firm) and Ernst & Young (a North American consulting firm) have perceived their knowledge management activities as strategic for past merger success. They consider gathering, selecting, filtering, analyzing, and disseminating internal and external knowledge as critical to their business models (e.g., satisfying their customer's needs and improving sales) (Lara et al. 2010).

Information technology (IT) enables social interaction among the organization's members to share knowledge and apply it effectively in the firm's business activities (Mueller et al. 2011). IT support is thus a key facilitator of a firm's knowledge management (Pinjani & Palvia 2013). Siemens, for example, creates advantage from a sustainable knowledge network (Technoweb) created to solve daily operational problems. Siemens uses IT to manage internal collaboration and share knowledge among experts, facilitate real-time communication exchange, and find hidden knowledge to save work time and solve problems faster and more efficiently (Grau et al. 2004; Lakhani et al. 2015).

Using social media for business activities (i.e., beyond marketing) is a new corporate phenomenon, and our understanding of the Information Systems (IS) field is in the initial stages (Aral et al. 2013; Braojos et al. 2015a; Leidner et al. 2010). Incorporation of social media is thus almost a necessity in today's IS research. Social media may provide additional customer and industry data to digitally convert information into knowledge to innovate. Such incorporation may suggest a potential complementary role of social media in the relationships between IT, knowledge management, and innovation outcomes—the central thesis of this investigation. A counter-argument may be that the firm's employees may spend unproductive time on social media that could otherwise be used for knowledge exploitation and innovation, a phenomenon referred to as cyber-loafing (e.g., Glassman et al. 2015). If the firm manages social media appropriately, however, they can become a golden source of data. If they are integrated rationally into the firm's IT infrastructure, they can provide an excellent complement to knowledge exploration and exploitation to achieve more and better innovations. This theoretical argument needs more in-depth development and empirical testing, and our investigation aims to connect all pieces properly to complete the puzzle.

This research attempts to answer two key research questions: (1) Does IT infrastructure impact innovation performance through knowledge ambidexterity (i.e., the firm's ability to use a well-balanced combination of knowledge exploration and exploitation for operational purposes)? and (2) Can these relationships be strengthened in firms that have developed social media capability (i.e., the firm's ability to leverage social media to execute business activities)? This investigation thus examines both the impact of IT-enabled knowledge ambidexterity on innovation performance and the potential moderator role of social media capability. This research theorizes that IT infrastructure enables development of knowledge ambidexterity to increase innovation performance, and that social media capability may perform a moderator role in this equation. We test our theory using partial least squares (PLS) path modeling with a secondary dataset on a sample of 100 small U.S. firms.

This work makes several contributions to the field of IS. First, it provides new evidence to develop a different explanation of how IT infrastructure enables management of organizational knowledge to increase innovation performance than the explanation given in prior IS research, and develops this argument by focusing on knowledge ambidexterity in small firms. Second, the investigation develops the concept of social media capability for business activities and theorizes how this capability moderates the relationship between IT infrastructure and knowledge ambidexterity.

The remainder of the paper is organized as follows. Next, we discuss the literature review that informs this work. The third section explains the theories on which the proposed model is based and develops the hypotheses. The fourth and fifth sections present the research methodology (sample, data, and measures), empirical analysis, and results. Subsequently, the manuscript concludes with a discussion of the findings and implications of the research.

2. Literature review

2.1. IT, knowledge management, and innovation performance

Prior IS research has focused primarily on the effects of IT on knowledge management activities and performance (e.g., Choi et al. 2010; Real et al. 2006; Sabherwal & Sabherwal

2005; Tanriverdi 2005). Sabherwal and Sabherwal (2005) examine the effects of IT-based knowledge management announcements on short-term firm value. Tanriverdi (2005) focuses on large U.S. firms to examine how IT relatedness impacts financial performance through knowledge management capability. Choi et al. (2010) and Kettinger et al. (2015) explore the role of IT support in knowledge-sharing behavior and the possible impact of both on team performance.

Another major area of IS literature studies the relationship between IT and innovation activities, and performance (e.g., Chen et al. 2015; Kleis et al. 2012; Kumar & Bose 2016), as well as the relationship between knowledge management and innovation (e.g., Leal et al. 2014). For example, Kleis et al. (2012) posit that IT and research and development activities positively affect innovation production.

With a few exceptions (e.g., Eseryel 2014; Joshi et al. 2010), however, analysis of the impact of IT on knowledge management and innovation activities *in the same study* is very limited. On examining the effect of IT-enabled knowledge capabilities (potential and realized absorptive capacity) on firm innovation, Joshi et al. (2010) find that IT applications enable the firm to absorb knowledge to increase innovation outputs. Eseryel's (2014) case study illustrates that IT supports the firm's processes of knowledge creation (i.e., socialization, externalization, combination, and internalization) for open innovation activities. Our research differs in focusing on knowledge ambidexterity in small firms and tests empirically how IT infrastructure enables the exploration and exploitation of organizational knowledge to improve innovation performance. Knowledge ambidexterity refers to the firm's ability to use a well-balanced combination of exploration and exploitation of organizational knowledge for operational purposes (Durcikova et al. 2011; He & Wong 2004; Tushman & O'Reilly 1996; Voss & Voss 2013). Table 1 presents our comprehensive analysis of prior research on IT, knowledge management, and firm performance.

Table 1: Comprehensive analysis of prior research on IT, knowledge management, and firm performance

Authors	Source	Key finding(s)
Sabherwal and Sabherwal (2005)	Decision Sciences	Cumulative abnormal returns resulting from IT-based knowledge management announcements are greater when knowledge management is aligned with the firm's efficiency, and when the firm has greater stability, greater diversification, smaller size, and lower profitability
Tanriverdi (2005)	MIS Quarterly	IT relatedness has a positive effect on knowledge management capability, which in turn has a positive effect on the firm's financial performance
Choi et al. (2010)	MIS Quarterly	IT support has a positive impact on the development of transactive memory systems in teams. IT support and transactive memory systems have a positive impact on knowledge sharing and knowledge applications, which in turn impact team performance
Joshi et al. (2010)	Information Systems Research	IT provides a set of knowledge capabilities that contribute to firm innovation in different ways. IT applications enable the development of a potential absorptive capacity that in turn facilitates realized absorptive capacity, and the latter improves the development of new ideas (patents)
Kettinger et al. (2015)	European Journal of Information Systems	When people perceive strong IT support, they are likely to be confident in their information management skills and subsequently more likely to cue into a psychological climate that motivates knowledge sharing, which in turn promotes knowledge sharing

2.2. Social media, knowledge management, and innovation performance

The prior literature views social media technologies as supportive of the firm's knowledge management due to their presence and interactivity in assisting firms' knowledge management efforts (e.g., Mueller et al. 2011; Pan et al. 2015; Sultan 2013). For example, Mount and Garcia (2014) propose a four-step framework for social media use in business activities: scan, engage, learn, and internalize.

The new knowledge management era is becoming increasingly aware of online social media and cloud computing as enablers of knowledge, in some cases even as strategic sources of innovation (e.g., Bengtsson & Ryzhkova 2013; Leonardi 2014). Leonardi (2014), for example, provides a theory of communication visibility and asserts that firms can enhance meta-knowledge and foster improvements in innovativeness by implementing social media. Such use of social media for business activities (i.e., beyond marketing) is a new corporate phenomenon, and our understanding of it is in the initial stages (Aral et al. 2013; Braojos et al. 2015a). This topic has not received adequate attention in the IS research. Our paper analyzes the moderator role of social media in knowledge ambidexterity and innovation performance. Table 2 presents our comprehensive analysis of prior research on social media and business activities, which continues Braojos et al.'s (2015a) literature review.

Table 2: Comprehensive analysis of prior research on social media for business activities

Authors	**Source**	**Key finding(s)**
Beck et al. (2014)	MIS Quarterly	The firm's social media establish electronic networks of practices and foster knowledge exchange among employees. The individual characteristics of knowledge seekers and knowledge contributors impact the quality of knowledge exchanged
Leonardi (2014)	Information Systems Research	The firm's social media enhance communication visibility to improve meta-knowledge, fostering improvements in innovativeness
Mandviwalla and Watson (2014)	MIS Quarterly Executive	To generate capital from social media strategy, one must establish capital goals (what capital one wants to generate) and apply four complementary tactics to achieve the goals: (1) listening and branding, (2) mining and deciding, (3) conversing and sharing, and (4) co-creating and innovating
Mount and Garcia (2014)	MIT Sloan Management Review	Social media can enable the firm to conduct market research on a larger scale and facilitate brand rejuvenation. Converting the mass of user-generated content into knowledge requires a framework. This paper provides a four-step framework for social media use in business activities: scan, engage, learn, and internalize
Kane (2015)	MIS Quarterly Executive	The two fundamental social media capabilities are establishing social media and accessing digital content. These two capabilities influence employee performance and user behavior
Pan et al. (2015)	Information & Management	Social media support intensifies knowledge exchange among friends in a virtual community of practice

2.3. Knowledge management, organizational ambidexterity, and knowledge ambidexterity

Organizational ambidexterity refers to the firm's ability to manage tensions between exploratory and exploitative organizational behaviors (Benner & Tushman 2003; March 1991). Different literature streams, including organizational learning, technology and innovation management, strategy, and organizational theory, have contributed to the research on organizational ambidexterity. Building on the technology and innovation management literature, we can consider ambidextrous firms as organizations that excel at exploiting existing products (i.e., repetitive and incremental innovation)[1] and exploring new products (i.e., radical innovation)[2] (Tushman & O'Reilly 1996). Drawing on the organizational learning literature, March (1991) proposes that exploitation and exploration are two different learning activities. Whereas exploitation involves the set of practices implemented to make the most of new/existing knowledge, exploration indicates the set of practices that search and experiment with new knowledge. We draw on this body of literature to extrapolate organizational ambidexterity to the context of exploration and exploitation of organizational knowledge, generating the concept of knowledge ambidexterity.

Knowledge management is the continuous process of acquisition, creation, sharing, storage, (Mueller et al. 2011), and use of knowledge at firm level (e.g., Choi et al. 2010). The process starts with obtaining new knowledge. Codification of knowledge is needed to transfer knowledge easily and retain it in the firm, making it centrally available to organizational members (Sabherwal & Sabherwal 2005). The process continues with the transfer and sharing of the knowledge among the organization's members and ends with knowledge application, which enables organizational members to propose initiatives based on that knowledge to solve operational problems and increase competitiveness (Alavi & Leidner 2001).

Two critical concepts/phenomena from organizational learning should be highlighted: exploration and exploitation of knowledge. Knowledge exploration refers to the process of learning that helps the firm to acquire/create, share, assimilate, and store new knowledge. Knowledge exploitation is the process of learning that comes from reusing, transforming, applying, and leveraging existing/new knowledge in the firm (March 1991).

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[1]Repetitive innovation includes the repetition of existing design of existing products. Incremental innovation includes the creation of new design of existing products.
[2]Incremental innovation includes the development of new products to enter into new markets.

The literature on knowledge exploration-exploitation management contains two divergent schools of thought, involving tradeoffs versus complementarity strategies. The tradeoff strategy advocates specializing in either searching for and acquiring new knowledge (e.g., exploration) or controlling and improving existing/new knowledge (e.g., exploitation) (March 1991). Firms that prioritize exploitation are less able to adapt to changes, while firms that focus on exploration can lose efficiency because they cannot cover every new idea. Ambidexterity was born as the idea of simultaneously pursuing and balancing exploratory and exploitative practices to achieve better business performance. Ambidexterity theory thus considers exploration and exploitation as complementary strategies (Gupta et al. 2006; Kristal et al. 2010). Some scholars, such as Uotila et al. (2009) and Kim et al. (2012), analyze the tension and tradeoffs between exploitation and exploration implementation. Others examine the effect of ambidexterity on performance (e.g., He & Wong 2004; Lubatkin et al. 2006; Voss & Voss 2013). Lubatkin et al. (2006) examine whether a small-to-medium-sized firm's joint pursuit of exploration and exploitation enhances its performance. He and Wong (2004) study how exploration and exploitation can jointly affect firm performance in the context of technological innovation.

This investigation differs from prior research on IT, knowledge management, and firm performance by focusing on knowledge ambidexterity, the firm's ability to use a well-balanced combination of exploration and exploitation of organizational knowledge for operational purposes (e.g., Durcikova et al. 2011; He & Wong 2004)[3]. Table 3 presents our comprehensive analysis of prior literature on organizational ambidexterity.

[3]Although knowledge sharing may be a component of knowledge exploration and knowledge reusing may be a component of knowledge exploitation, knowledge ambidexterity is a more complex concept than simply sharing and reusing knowledge. Knowledge exploration refers to the process of learning that helps the firm to acquire/create, share, assimilate, and store new knowledge. Then, knowledge exploration includes more things

3. Theory and hypotheses

3.1. IT-enabled organizational capabilities and the organizational learning framework

The IT-enabled organizational capabilities perspective argues that IT enables firms to generate business value through intermediate organizational capabilities such as flexibility, supply chain integration, talent management, organizational learning, and knowledge management (e.g., Ajamieh et al. 2016; Benitez et al. 2015; Benitez et al. forthcoming). For example, Chen et al. (2017) examine the impact of IT on firm performance through strategic flexibility. They find that IT support for core capabilities positively affects strategic flexibility to increase firm performance. This work draws on the IT-enabled organizational capabilities literature to theorize that firms that develop IT infrastructure capability and leverage it to explore and exploit organizational knowledge can generate significant innovation performance gains.

apart from sharing knowledge (i.e., acquisition/creation and store knowledge). Knowledge exploitation indicates the process of learning that comes from reusing, transforming, applying, and leveraging existing/new knowledge in the firm (March 1991). Then, knowledge exploitation includes reusing knowledge, but also includes transforming, applying, and leveraging existing/new knowledge.

Table 3: Comprehensive analysis of prior research on organizational ambidexterity

Authors	**Source**	**Key finding(s)**
Tushman and O'Reilly (1996)	California Management Review	Superior firm performance is expected from ambidextrous firms, which simultaneously pursue incremental and discontinuous innovation. To become ambidextrous, it is essential that the firms have a decentralized structure, a common culture, and a supportive leadership
Gibson and Birkinshaw (2004)	Academy of Management Journal	The firm's context affects ambidexterity (the ability to achieve both alignment and adaptability simultaneously), which in turn affects performance
He and Wong (2004)	Organization Science	The interaction between exploratory and exploitative innovation strategies is positively related to sales growth rate
Gupta et al. (2006)	Academy of Management Journal	Theoretical paper addressing four issues: definitions and connotations of exploration and exploitation, orthogonality versus continuity, ambidexterity versus equilibrium, and duality versus specialization
Lubatkin et al. (2006)	Journal of Management	Managerial behavioral integration is essential to achieving ambidextrous orientation in small-to-medium-sized firms. Joint pursuit of an exploratory and exploitative orientation positively affects firm performance
Raisch and Birkinshaw (2008)	Journal of Management	This theoretical paper on the evolution of business ambidexterity research provides a synthesis of organizational ambidexterity research and areas for future research
Durcikova et al. (2011)	Information Systems Research	In a culture of innovation with the absence of knowledge management systems, analysts are more able to reuse solutions (exploit) than to explore new solutions. The opposite occurs in a climate of autonomy, where analysts are more likely to innovate (explore) than to reuse solutions. In the presence of knowledge management systems, innovation culture enhances solution innovation, and a climate of autonomy diminishes it
Patel et al. (2013)	Academy of Management Journal	A complementary set of human resource management practices enables a high-performance work system that helps to develop the resource flexibility necessary to produce ambidexterity to increase firm growth
Voss and Voss (2013)	Organization Science	Strategies based on product and market exploration, product and market exploitation, and a combination of market exploration and product exploitation positively affect firms' revenues

Organizational learning is one of the theoretical frameworks used in prior research to conceptualize and explore organizational ambidexterity (e.g., Raisch & Birkinshaw 2008). Organizational learning is the dynamic process of creating knowledge through individuals' and groups' interaction to pursue organizational renewal (Crossan & Berdrow 2003). This process requires creating new knowledge, explaining and codifying the new knowledge, sharing and transferring this knowledge within the firm, and embedding this knowledge through rules, norms, procedures, and forms. The resulting organizational knowledge is diffused to individuals to be leveraged (March 1991). Exploration and exploitation are differentiated by the level of learning (e.g., Benner & Tushman 2003; Gupta et al. 2006) A well-balanced combination of organizational knowledge exploration and exploitation (i.e., types of learning) helps to achieve long-term business benefits (Raisch & Birkinshaw 2008). We use the organizational learning framework to conceptualized knowledge ambidexterity and explain how knowledge ambidexterity can lead to better innovation performance.

3.2. IT infrastructure and knowledge ambidexterity

IT infrastructure capability is the firm's ability to leverage its technical and human IT resource infrastructure (Benitez & Ray 2012; Benitez et al. forthcoming; Melville et al. 2004) to acquire/provide accurate and timely information from/to key organizational members (Mithas et al. 2011; Pavlou & El Sawy 2006). Based on Melville et al.'s (2004) theoretical framework, IT infrastructure includes two components: technical IT resource infrastructure and human IT resource infrastructure. Technical IT resource infrastructure includes servers, computers, laptops, operating systems, software, electronic communication networks (email, Intranet, Extranet, and wireless devices), and shared customer databases (Aral & Weill 2007; Benitez & Ray 2012). Human IT resource infrastructure refers to the IT and business skills of IT managers and employees (Benitez et al. forthcoming; Byrd & Turner 2001).

IT infrastructure can enable knowledge ambidexterity in the firm. First, IT infrastructure can affect knowledge exploration. The ability to acquire/share information from/to the market enabled by IT infrastructure can facilitate acquisition/creation of new organizational knowledge. IT technical and human resource infrastructure supports the firm to manage information better and facilitates the conversion of information into useful new knowledge (Mithas et al. 2011), enabling knowledge exploration. For example, Google continuously collects a huge amount of web-based market data (i.e., knowledge) for analysis. Based on this new knowledge, Google makes accurate predictions about the market (Coles et al. 2007).

IT infrastructure capability also helps the firm to internally share new knowledge through interpersonal relationships (Pavlou & El Sawy 2006). IT improves communication within the firm. This is the case of Ernst and Young's Intranet, where consultants have online discussions, providing immediate access to collective knowledge (Lara et al. 2010). IT infrastructure capability can help the firm to store and assimilate new knowledge. IT infrastructure facilitates information update (e.g., identifying industry trends, customer interests, or competitor movements) (Joshi et al. 2010). By facilitating access to stored information enhances interpretation and synthesis of information, thus enabling knowledge exploration (Pavlou & El Sawy 2006).

Second, IT infrastructure can enable knowledge exploitation in the firm. IT infrastructure provides the firm with IT tools to improve both coordination of the supply chain (i.e., upstream suppliers and downstream customers) and flexibility to reuse, transform, apply, and leverage new/existing organizational knowledge rapidly (Benitez & Ray 2012; Chen et al. 2017), enabling knowledge exploitation. In addition, IT infrastructure improves intra-firm coordination by enabling cross-functional collaboration within the firm (Kettinger et al. 2015) to facilitate knowledge exploitation. For example, Mercadona (a leading Spanish retailer) often leverages its technical IT resource infrastructure to better coordinate its new product development unit to convert a sensed potential customer need (i.e., market and customer knowledge) into a potential new product development (i.e., knowledge transformation and application, or knowledge exploitation) (Benitez et al. 2015).

In summary, IT infrastructure facilitates the acquisition and management of information both inside and outside the firm, facilitating acquisition/creation of new useful knowledge, and more efficient application and leveraging of the new/existing knowledge. Hence, it is rational to hypothesize that:

Hypothesis 1 (H1): There is a positive relationship between IT infrastructure and knowledge ambidexterity.

3.3. Knowledge ambidexterity and innovation performance

Innovation performance refers to the outcomes of the process of making changes in existing products/processes and/or to the development of new products/processes arising from internal and external knowledge (De Souza et al. 2016; Joshi et al. 2010; Kleis et al. 2012).

Knowledge ambidexterity can facilitate innovation performance. Overall, knowledge capabilities help the firm to understand complex technical knowledge, contributing to creation of new innovations (e.g., Joshi et al. 2010). Ability to innovate may in fact be considered as one of the critical contributions of knowledge management (e.g., Busquets 2010) which may develop from knowledge ambidexterity. Ambidextrous firms can continuously improve current processes and obtain novel alternatives (Raisch & Birkinshaw 2008), as ambidextrous new product teams are more efficient and better able to understand the market more quickly, enhancing the effectiveness of new product development tasks (e.g., Lubatkin et al. 2006). Thus, firms that both explore and exploit can maximize their innovations (Kim et al. 2012).

Knowledge exploration can improve innovation performance. Acquisition/creation and sharing of new knowledge within/beyond the firm’s boundaries brings more new knowledge elements into the firm, increasing the potential number of architectural innovations (Henderson & Clark 1990). For example, the interaction and collaboration of different backgrounds and expertise among supply chain partners enable the firm to acquire new knowledge to develop new products (Schoenherr et al. 2014). This capability can propel creative thinking and idea sharing in the firm, improving innovation performance (e.g., Lubatkin et al. 2006). Moreover, exploration enables access to different technological areas, adding diversity and heterogeneity that aid in new knowledge creation, and this new knowledge may be used to create more impactful innovations.

On the other hand, firms that reuse, apply, and leverage existing/new knowledge (i.e., knowledge exploitation) better can outperform competitors in terms of more effective changes in existing products/processes, improving the firm's innovation performance. Using the same knowledge repeatedly increases the level of experience and understanding of the product's requirements, facilitating the task of product development (Eisenhardt & Tabrizi 1995). Repeated use of knowledge elements also allows better assimilation and identification of the firm's valuable knowledge (i.e., knowledge identification), a critical antecedent to applying and leveraging knowledge, which may in turn positively affect innovation results (e.g., Katila & Ahuja 2002).

Finally, prior empirical research finds that a firm's exploration and exploitation capabilities have a positive impact on new product development (Gupta et al. 2006; Newell 2015). A clarifying example is how Nivea (a leading global skin care firm) explores and exploits knowledge to increase its innovation performance. Nivea has conducted sessions to acquire new knowledge from customers and experts on different topics, such as the problem of deodorants that stain the clothes. These sessions resulted in an anti-stain innovation, a new impactful product "black and white deodorant" that does not stain clothes. The firm analyzes data from existing sources, structuring and translating the data into useful knowledge through mechanisms such as group discussions or brainstorming that have generated new customer-oriented products (Lakhani et al. 2014). We thus hypothesize the following relationship:

Hypothesis 2 (H2): There is a positive relationship between knowledge ambidexterity and innovation performance.

3.4. Business value of social media: The moderator role of social media capability

3.4.1. The moderator role of social media capability in the relationship between IT infrastructure and knowledge ambidexterity

Social media capability refers to the firm's ability to leverage the social media platforms of Facebook, Twitter, and corporate blogs to execute business activities (Braojos et al. 2015a). This investigation argues that the relationship between IT infrastructure and knowledge ambidexterity can be stronger in the presence of social media capability; that is, social media capability can perform a positive moderator role in this relationship. Examining this role is the first way we explore how social media capability may potentially help the firm to create business value (i.e., impact innovation/firm performance).

Social media capability provides a vast amount of data on the market (customers and industry) that may be used to explore and exploit knowledge digitally. Social media provide a platform for organizational members to contact each other with continuous inflow and outflow of users (e.g., Ku et al. 2013), facilitating superior and faster information flows both within the firm and in interaction with suppliers and customers/the market (Sultan 2013). Such large data, more visible communication, and superior information flows enabled by social media (Limaj et al. 2016) increase opportunities to leverage IT resources to explore and exploit new/existing knowledge. For example, organizational members can acquire customer insights/feedback (i.e., new knowledge) from the firm's Facebook and Twitter sites and better assimilate this new knowledge through the firm's databases and the enterprise resource planning system, enabling knowledge exploration.

In summary, firms with social media capability will capture fine-grained data on the market that can be integrated into the firm's IT infrastructure to explore and exploit knowledge for business benefits. It is thus rational to expect that IT infrastructure and social media capability can work together to explore and exploit knowledge:

Hypothesis 3a (H3a): Social media capability positively moderates the relationship between IT infrastructure and knowledge ambidexterity.

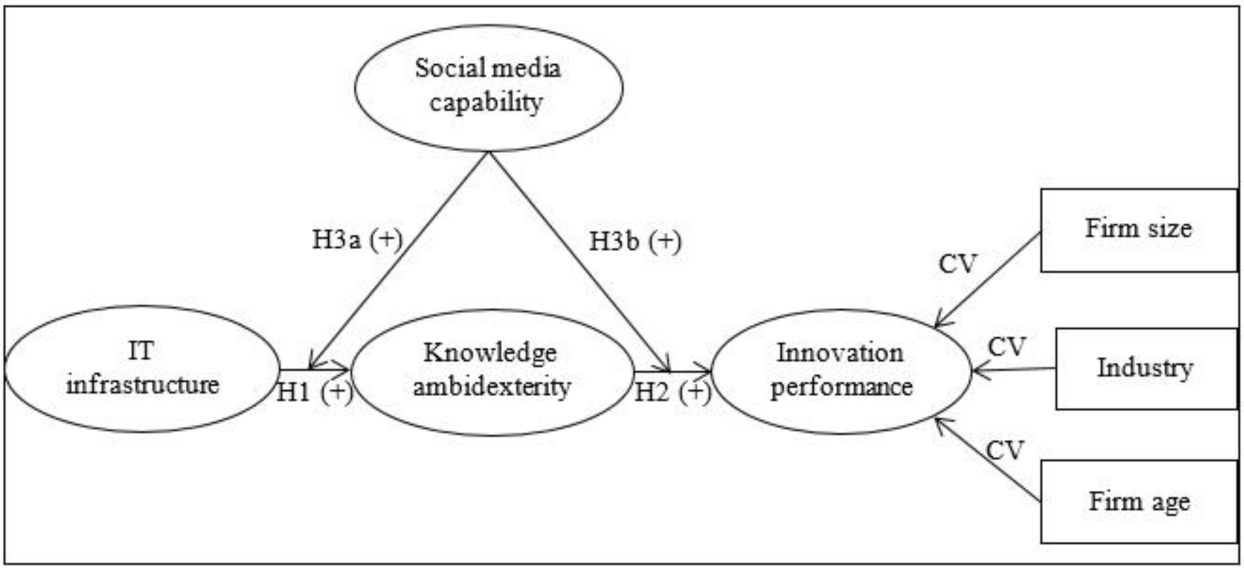
3.4.2. The moderator role of social media capability in the relationship between knowledge ambidexterity and innovation performance

We argue that social media capability can also positively moderate the relationship between knowledge ambidexterity and innovation performance. This moderation is the second way we propose that social media capability may potentially help the firm to create business value. First, social media are valuable tools for managing knowledge effectively within firms (Sultan 2013; Templeton et al. 2012), as they facilitate relationships and exchange of ideas, enhancing innovativeness (Kim et al. 2011). For example, Danone has implemented IT-based knowledge management programs (e.g., Who's Who and Dan 2.0), through which employees can interact in performing job tasks. Dan 2.0 is an internal social media platform that helps Danone to convert organizational knowledge into innovative solutions to solve problems, suggesting that social media capability reinforces the effect of knowledge ambidexterity on innovation performance. For example, when Danone launched biscuits in Finland, it did not know that Finns did not eat biscuits for breakfast. Thanks to IT-based knowledge sharing from LU France to LU Norway employees, the company repositioned the campaign to market the biscuit as a snack for mid-morning hunger, enabling Danone to maximize its marketing campaign (Beyersdorfer et al. 2011; Edmondson et al. 2008).

Second, social media empower the organization's members and customers to engage in the firm's knowledge management activities, enabling open innovation (Joshi et al. 2010). Such is the case of Siemens, which performed several knowledge-based open innovation projects both inside (with employees) and outside the firm (with suppliers and customers) using social media. One of these open innovation projects was run by OSRAM (a subsidiary of Siemens), which designed an open online contest that offered monetary prizes to participants with the best new and creative customer-oriented LED light solution. Participants could submit their ideas and evaluate or comment on other solutions. A total of 952 participants provided 576 ideas, ranging from children's toys to garden accessories. Finally, Siemens selected two of the 576 ideas and considered them for commercialization (Lakhani et al. 2015). In summary, since social media provide additional market data and knowledge to the firm on how to convert knowledge management efforts into more and better innovations, it is probable that ambidextrous firms will manage knowledge to transform new/existing knowledge into new products/processes more easily if they also have proficiency in social media. We therefore hypothesize the following:

Hypothesis 3b (H3b): Social media capability positively moderates the relationship between knowledge ambidexterity and innovation performance.

Figure 1: Conceptual model (CV = Control variable)



4. Research methodology

4.1. Sample

We empirically tested the proposed model with a sample of the 100 small firms included in the 2013 Forbes America's Best Small Companies ranking (in short, the Forbes database), which includes the best 100 publicly recognized U.S. small firms with sales under one billion dollars (Braojos et al. 2015a). We analyzed all firms included in this ranking. The firms included in the sample came from 30 industries: consulting (18 firms), IT (16), food manufacturing (7), semiconductor manufacturing (6), healthcare (5), chemical (5), and other industries (43). Prior IS research contextualizes several types of studies of IT value in a sample of firms included in well-known rankings (like the ranking used in this study) (e.g., Benitez & Walczuch 2012; Benitez et al. 2015; Bharadwaj 2000; Braojos et al. 2015a; Joshi et al. 2010), confirming the logic of our decision.

This work focuses on small firms for two reasons. First, leveraging social media to explore and exploit knowledge remains crucial because small firms have a smaller portfolio of financial resources than large firms with which to compete effectively in the market (Braojos et al. 2015a). Second, prior research on IT, knowledge management, and innovation activities (e.g., Joshi et al. 2010) focuses on large firms. This work contributes to the field of IS by focusing on the moderator role of social media capability, a role not previously explored in similar research, and to do so by focusing on small firms.

4.2. Data and measures

To measure the constructs included in the proposed model, we collected and used a secondary dataset drawn from eight different databases. We first collected the data from the 2013 Forbes database and then used the name of each firm to gather information from the other databases.

4.2.1. IT infrastructure

Structured content analysis was performed of the firms' 2013 and 2014 annual reports collected from the U.S. Securities and Exchange Commission Filling database. The analysis measured IT infrastructure as a two-indicator composite[4] first-order construct composed of

[4]A clear distinction can be done between behavioral constructs and design artifacts (Benitez et al. 2017; Henseler 2017). While behavioral constructs are usually modeled as common factor models, composite-formative (in short, composite) should be the preferred choice for design artifacts. These artifacts can be understood as theoretically justified constructions which consist of more elementary components. They are human-made

the accumulated total number of the firm's initiatives on mentions of technical and human IT resource infrastructure in 2013 and 2014 (Joshi et al. 2010; Luo et al. 2012). We used a list of 35 keywords on technical and human IT resources drawn from Braojos et al. (2015a, 2015b) and read the resulting paragraph carefully, computing each keyword—one per paragraph—where it appears (Table 4). Structured content analysis is a well-established method in IS research (e.g., Palvia et al. 2015).

4.2.2. Knowledge ambidexterity

Structured content analysis was also conducted to measure the knowledge ambidexterity construct. Joshi et al. (2010) provided a list of 18 critical keywords related to IT applications that enable knowledge management activities and measured knowledge management capability as the accumulated total number of a firm's IT applications that enable knowledge management activities, using information from the LexisNexis and Knowledge Management World databases. Knowledge Management World is a business magazine covering news on how IT is used to develop business knowledge activities/capabilities. We adopted the same measure scheme to measure knowledge ambidexterity with information from the LexisNexis and Knowledge Management World databases in 2013 and 2014. The coding process consisted of carefully reading the news on these 18 keywords published in 2013 and 2014, and deciding whether the firm used/applied the specific IT application or not, distinguishing between IT applications that helped the firm to acquire, share, assimilate, and store knowledge (i.e., to explore knowledge), and those that helped the firm to reuse, apply, and use organizational knowledge (i.e., to exploit knowledge) (Joshi et al. 2010). A total of 227 and 22 news items were identified for knowledge exploration and knowledge exploitation,

objects that are typically created by managers, staff, or the firm itself, and should be modeled as composite. The composite artifact serves as proxy for the concept under investigation and can be understood as a mix of ingredients (indicators/dimensions) forming the recipe (composite artifact) (Benitez et al. forthcoming; Henseler 2015, 2017; Rueda et al. forthcoming). All the constructs/artifacts of this research were modeled as composite.

respectively. Knowledge ambidexterity was measured as a two-indicator composite first-order construct determined by knowledge exploration and exploitation.

Table 4: List of initiatives/mentions on the firm's IT infrastructure

IT infrastructure component	References	Keywords
Technical IT resources	Aral and Weill (2007), Luo et al. (2012), Braojos et al. (2015a, 2015b)	Information technology (IT) Information System (IS) Computer/personal computer (PC) Laptop Operating system Data center Server Web/web site Network Internet Intranet Electronic media Online E-commerce/ecommerce E-mail/email Database/data Software Enterprise resource planning (ERP) Supply chain management (SCM)/SCM system Customer relationship management (CRM)/CRM system Data mining/data-mining system Business intelligence
Human IT resources	Byrd and Turner (2001), Benitez and Ray (2012), Luo et al. (2012), Braojos et al. (2015a, 2015b)	IT IS IT manager/management Chief Information Officer (CIO) Chief Technology Officer (CTO) IT Vice President IT leadership IT skills IT expertise IT employee/worker/workforce Helpdesk IT training IT solution

4.2.3. Social media capability

Social media capability was measured as a second-order construct determined by Facebook capability, Twitter capability, and blog capability (Braojos et al. 2015a, 2015b) with data collected in June 2014. Social media capability was specified as composite at both first- and second-order level.

We evaluated Facebook capability through a number of past or future events, experience, and updates using data collected from the firm's Facebook site. Following Braojos et al.

(2015a), we measured the firm's experience on Facebook as the average number of months that the firm had operated on Facebook, and its updates by scoring, where 1 indicated a low and 5 a high degree of content updating in this platform. Each firm was given a score from 1 to 5 based on whether the firm had made a comment on Facebook more than one month ago/in the last month/in the last two weeks/in the last week/in the last two days, respectively.

Twitter capability was measured in terms of the time spent writing tweets, experience, and updates using data collected from the firm's Twitter site and the Twopcharts database (http://twopcharts.com/). The time spent writing tweets was measured as the average hours that firm had spent writing tweets. Experience and updates were measured by the same method we used to measure Facebook. Blog capability was measured through the firm's experience and updates on blogs with data collected from the firm's blog site.

4.2.4. Innovation performance

Innovation performance, the key endogenous variable in this work, was measured with information collected from the U.S. Patent and Trademark Office database in the period 2007–2014, as follows. First, we estimated a patent quality-weighting ratio (PQWR) by dividing the number of citations received by the firm's patents for one year from subsequent patents within a three-year window by the number of patents it published in a year (Kleis et al. 2012). We used the three-year window to avoid vintage effects of older patents (Kleis et al. 2012). This procedure weighted the number of patents in a year by the number of citations that these patents had received in the following three years, providing a patent measure that focuses on quality, not only number, of patents. We estimated a PQWR for 2007–2010, 2008–2011, 2009–2012, 2010–2013, and 2011–2014. For example, the 2007–2010 PQWR was estimated by dividing the number of citations received by the firm's 2007 patents from subsequent patents within the period 2008–2010 by the number of patents the firm published in 2007.

Second, based on these PQWR values, we built a ranking of firms by industry, in which a higher PQWR indicated a better position. We then calculated the rate of sectoral excellence (RSE) in innovation based on the firm's ranked position in its industry (Benitez & Walczuch 2012; Benitez & Ray 2012). RSE was estimated as follows: RSE = 1 - (Firm's position in its industry in our PQWR ranking/Total number of firms in each industry in our PQWR ranking). This procedure generated five indicators of RSE in innovation for 2007–2010, 2008–2011, 2009–2012, 2010–2013, and 2011–2014 for each firm included in the sample. These indicators were then used as five composite indicators to measure innovation performance (i.e., a first-order construct).

4.2.5. Control variables

We controlled for the effects of firm size, industry, and firm age on innovation performance with information collected from the 2013 and 2014 Forbes database. Firm size was measured as the natural logarithm of the average number of employees in 2013 and 2014 (Benitez & Walczuch 2012). We measured industry as a dummy variable (0: Manufacturing firm, 1: Service firm). Firm age was measured as the natural logarithm of the number of years operating in its industry in 2014 (Chen et al. 2015).

5. Empirical analysis and results

We tested the proposed model empirically by using PLS path modeling, a variance-based SEM technique (Benitez et al. 2017; Henseler et al. 2016; Marcoulides et al. 2009), with the statistical software package Advanced Analysis for Composites (ADANCO) 2.0 Professional (http://www.composite-modeling.com/) (Henseler & Dijkstra 2015). ADANCO is modern software for variance-based SEM. It models composites, common factors, and single-indicator constructs and facilitates causal and predictive modeling.

It is appropriate to use PLS in this research, first, because our constructs are specified as composite and PLS is particularly well suited to give consistent estimations for this type of model (Becker et al. 2013; Benitez et al. 2017; Henseler et al. 2014; Rigdon et al. 2014; Sarstedt et al. 2016). Second, PLS is particularly advisable for estimating models that employ secondary data, the case of our model (Gefen et al. 2011; Rigdon 2013). Third, variance-based SEM techniques provide better results than covariance-based SEM techniques when estimating very complex models (i.e., those with multidimensional constructs) (e.g., Hair et al. 2012; Roldan & Sanchez 2012). PLS SEM has also been used widely in the field of IS (Benitez et al. 2017; Ringle et al. 2012; Roldan & Sanchez 2012).

Prior to data collection, we performed a statistical power analysis. The maximum number of predictors in the proposed model was six (the number of structural links received by innovation performance in the proposed model). Assuming a medium effect of size (f^2 = 0.150), the proposed model required a minimum sample size of 97 to achieve a power of 0.800 and an alpha level of 0.05 (Cohen 1988). Our sample size was 100, adequate to estimate the proposed model. This analysis suggested that our study had sufficient statistical power to detect the effect of interests.

5.1. Measurement model evaluation

IT infrastructure, knowledge ambidexterity, and innovation performance are composite first-order constructs, whereas social media capability is a composite second-order construct. Composite constructs at the first- and second-order level should be evaluated by assessing multicollinearity, weights, and loadings, as well as their level of significance (Benitez & Ray 2012; Cenfetelli & Bassellier 2009).

We evaluated the multicollinearity of our indicators/dimensions by estimating the variance inflation factors (VIFs), which ranged from 1.112 to 16.041. All VIF values were below 3.3 except those of the construct IT infrastructure (16.041 in the two indicators), and two indicators of innovation performance. Based on the high correlation between these four indicators, we used the correlation weights (mode A) in the estimation of all constructs of the proposed model instead of the regression weights (mode B) to increase stability.

A bootstrap analysis with 5000 subsamples (Petter et al. 2007; Barroso et al. 2010; Hair et al. 2011) showed that the indicator/dimension weights and loadings were significant for all constructs except for the weight of one indicator of innovation performance (i.e., RSE 2008–2011). This composite indicator was retained because its loading was significant (Benitez & Ray 2012; Braojos et al. 2015b; Cenfetelli & Basellier 2009).

Social media capability, a multidimensional construct, was estimated through the two-step approach (Chin 2010). In the first step, we freely correlated all first-order constructs to obtain the latent variable scores of the dimensions. In the second step, the latent variable scores were used as the measures of the multidimensional construct (i.e., social media capability) (Wang et al. 2015). Table 5 shows the details of the measurement model properties.

Finally, we tested the external validity of all composites by conducting a confirmatory composite analysis of the saturated model (Benitez et al. 2017; Henseler et al. 2014; Henseler et al. 2016). Confirmatory composite analysis checks the adequacy of the composite models by comparing the empirical correlation matrix with the model-implied correlation matrix of the saturated model. This analysis can detect errors in the assignment of indicators to constructs or in the number of constructs (i.e., model misspecification) (Henseler et al. 2014). Table 6 shows the results for the first- and second-order models. Neither model should be rejected based on an alpha level of 0.05, since all discrepancies are below the 95%-quantile of the bootstrap discrepancies. These results suggest empirical support for this structure of composites at the first- and second-order levels. Overall, the proposed model presented very good measurement properties, implying that we could proceed with structural model assessment.

Table 5: Measurement model evaluation at first- and second-order levels

Construct/dimension/indicator	Mean	S.D.	VIF	Weight	Loading
IT infrastructure	83.440	82.400			
IT infrastructure 2013	79.610	81.384	16.041	0.511***	0.992***
IT infrastructure 2014	87.270	83.638	16.041	0.497***	0.992***
Knowledge ambidexterity	1.525	5.684			
Knowledge exploration	2.580	7.761	1.412	0.622***	0.901***
Knowledge exploitation	0.470	1.573	1.412	0.516***	0.852***
Social media capability					
Facebook capability: Facebook activity of the firm in terms of:			2.352	0.426*	0.891***
Number of events	5.510	18.549	1.112	0.290***	0.564***
Experience	33.773	25.581	2.126	0.460***	0.893***
Updates	2.740	2.223	2.088	0.478***	0.890***
Twitter capability: Twitter activity of the firm in terms of:			2.622	0.358*	0.898***
Time spent writing tweets	17.280	32.149	1.307	0.315***	0.702***
Experience	35.752	27.651	2.114	0.457***	0.888***
Updates	2.750	2.285	2.254	0.417***	0.895***
Blog capability: Blog activity of the firm in terms of:			1.594	0.369*	0.810***
Experience	17.266	31.681	1.847	0.526***	0.909***
Updates	1.255	1.949	1.847	0.566***	0.922***
Innovation performance	0.146	0.298			
RSE 2007–2010	0.140	0.299	2.881	0.194*	0.806***
RSE 2008–2011	0.157	0.308	2.625	0.150	0.761***
RSE 2009–2012	0.143	0.299	4.577	0.258***	0.905***
RSE 2010–2013	0.122	0.278	6.948	0.251***	0.950***
RSE 2011–2014	0.167	0.309	2.966	0.295**	0.877***
Firm size: Natural logarithm of the total number of full-time employees	6.951	1.238			
Industry: Manufacturing vs. service	0.480	0.502			
Firm age: Natural logarithm of the number of years of the firm's operations	3.384	0.573			

Note: A two-tailed test was used for the statistical inference of weights and loadings.

Table 6: Results of the confirmatory composite analysis (saturated model)

Discrepancy	First-order constructs			Second-order construct		
	Value	**HI_{95}**	**Conclusion**	**Value**	**HI_{95}**	**Conclusion**
SRMR	0.061	0.157	Supported	0.009	0.052	Supported
d_{ULS}	0.574	3.777	Supported	0.001	0.027	Supported
d_G	0.481	23.348	Supported	0.001	0.020	Supported

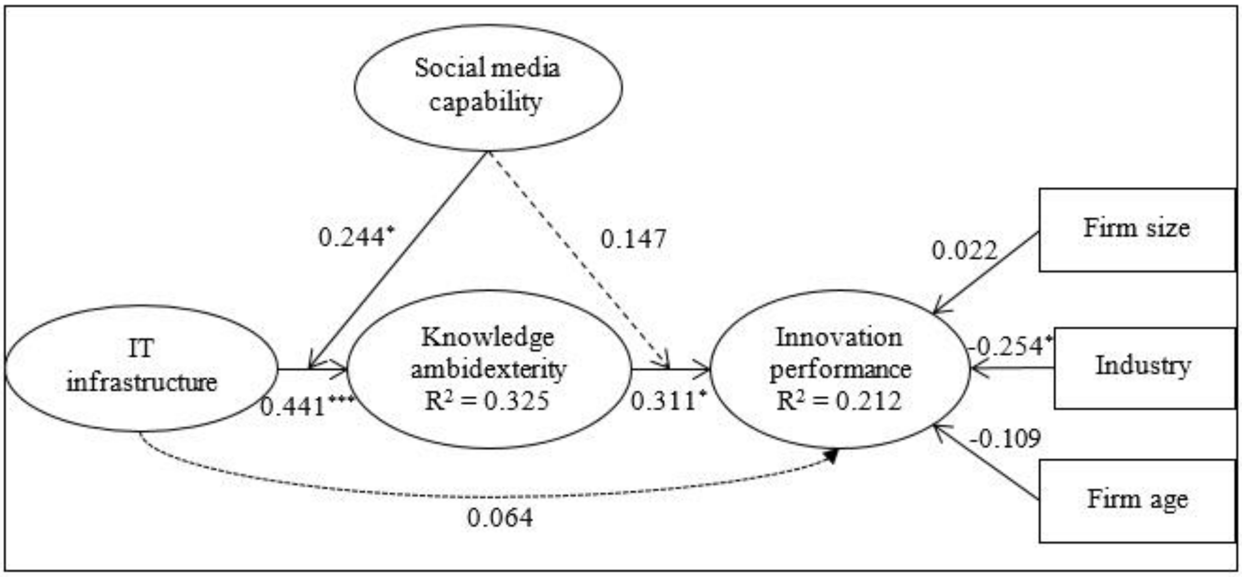
5.2. Structural model assessment

To test the hypothesized relationships, we evaluated the beta coefficients and significance of the proposed relationships (Henseler et al. 2016) by running a bootstrap analysis with 5000 subsamples. The effect size and R^2-values of the proposed relationships were also evaluated. We considered three models under study. To test the two first hypotheses (i.e., H1 and H2), we evaluated a baseline model that describes all direct effects on endogenous constructs, including all control variables and excluding social media capability. Model 1 includes in the prior model a link between social media capability and knowledge ambidexterity and a link between social media capability and innovation performance. Model 2 adds the interaction terms to model 1 (Felipe et al. 2016) to test H3a and H3b. We find support for all proposed hypotheses except H3b. The empirical analysis suggests that IT infrastructure enables knowledge ambidexterity (H1) (β = 0.508, $p_{\text{one-tailed}}$ < 0.001) and that this relationship is amplified more intensely when the firm leverages social media for operational purposes (H3a) (β = 0.244, $p_{\text{one-tailed}}$ < 0.05), suggesting that social media capability plays a positive moderator role in this relationship. Similarly, knowledge ambidexterity increases innovation performance (H2) (β = 0.333, $p_{\text{one-tailed}}$ < 0.01). Contrary to our expectations, the moderator role of social media capability in this relationship (H3b) is not significant (β = 0.147, $p_{\text{one-tailed}}$ > 0.10, confidence interval: −0.326, 0.349). Future research on social media should explore this relationship. Table 7 and Figure 2 present the results of the test of hypotheses.

The R^2-values for these relationships were 0.258 and 0.177 for baseline model, 0.265 and 0.191 for model 1, and 0.325 and 0.212 for model 2. The effect size (f^2) values of the key relationships of the proposed model ranged from 0.100 to 0.348 for the baseline model, from 0.092 to 0.187 for model 1, and from 0.027 to 0.198 for model 2, indicating weak-to-large effect sizes between the exogenous and endogenous variables in the proposed theory

(Henseler & Fassott 2010). Table 7 presents an effect size analysis for all relationships included in the proposed model.

Figure 2: Results of the test of hypotheses[5]



Goodness of model fit for the structural model was evaluated as in the confirmatory composite analysis described above, by examining the standardized root-mean-squared residual (SRMR), unweighted least squares (ULS) discrepancy (d_{ULS}), and geodesic discrepancy (d_G) for all models estimated (Henseler et al. 2014). This measure of goodness of fit evaluates the discrepancy between the empirical correlation matrix and the model-implied correlation matrix of the estimated model(s) (Benitez et al. 2017; Henseler 2015). The lower the values, the better the fit between the proposed model and the data (Benitez et al. forthcoming; Henseler & Dijkstra 2015). Overall, the SRMR value should be lower than 0.080 to accept the fit between the proposed model and the data. All discrepancies should be below the 95%-quantile of the bootstrap discrepancies (Henseler et al. 2014). As the SRMR value of the proposed model was 0.059 and all discrepancies were below the 95%-quantile of the bootstrap discrepancies, the proposed model should not be rejected based on the alpha

[5]Figure 2 presents the results of the model 2. 0.244* and 0.147 refer to the beta coefficients of the interaction terms between IT infrastructure and social media capability and between knowledge ambidexterity and social media capability, respectively. The effects from social media capability to knowledge ambidexterity (β = 0.119) and from social media capability on innovation performance (β = 0.160) have been omitted in this figure in sake of parsimony.

level of 0.05, which suggests very good model fit (see Table 7). Overall, the proposed model shows good structural model fit between the model and data (Henseler & Dijkstra 2015). Table 8 presents the correlation matrix.

Table 7: Structural model assessment and test of robustness

Beta coefficient	**Baseline model**	**Model 1**	**Model 2**	**Alternative model 1**	**Alternative model 2**
IT infrastructure → Knowledge ambidexterity (H1)	0.508^{***} (6.330) [0.339, 0.661]	0.448^{***} (3.661) [0.184, 0.662]	0.441^{***} (4.152) [0.204, 0.612]		0.343^{*} (2.263) [-0.016, 0.567]
Knowledge ambidexterity → Innovation performance (H2)	0.333^{**} (2.533) [0.055, 0.572]	0.318^{*} (2.274) [0.013, 0.564]	0.311^{*} (1.960) [-0.073, 0.541]	0.306^{*} (2.070) [-0.005, 0.579]	
IT infrastructure * Social media capability → Knowledge ambidexterity (H3a)			0.244^{*} (1.960) [-0.056, 0.459]		0.236^{*} (2.106) [-0.045, 0.436]
Knowledge ambidexterity * Social media capability → Innovation performance (H3b)			0.147 (0.750) [-0.326, 0.349]		
IT infrastructure → Innovation performance	0.147 (1.304) [-0.067, 0.375]	0.067 (0.568) [-0.170, 0.293]	0.064 (0.527) [-0.163, 0.319]	0.066 (0.544) [-0.171, 0.300]	
Social media capability → Knowledge ambidexterity		0.107 (1.023) [-0.042, 0.369]	0.119 (1.196) [-0.029, 0.363]		0.085 (0.765) [-0.088, 0.332]
Social media capability → Innovation performance		0.144 (1.158) [-0.097, 0.391]	0.160 (1.289) [-0.104, 0.390]	0.148 (1.127) [-0.126, 0.396]	
Firm size → Innovation performance	0.038 (0.441) [-0.130, 0.203]	0.036 (0.424) [-0.133, 0.198]	0.022 (0.255) [-0.134, 0.199]	0.032 (0.382) [-0.141, 0.188]	
Industry → Innovation performance	-0.292^{*} (-2.344) [-0.513, -0.029]	-0.275^{*} (-2.323) [-0.483, -0.024]	-0.254^{*} (-2.081) [-0.490, -0.014]	-0.266^{*} (-2.312) [-0.475, -0.027]	
Firm age → Innovation performance	-0.136 (-1.454) [-0.319, 0.049]	-0.122 (-1.339) [-0.298, 0.061]	-0.109 (-1.202) [-0.277, 0.074]	-0.122 (-1.323) [-0.291, 0.067]	
Knowledge ambidexterity → IT infrastructure				0.352^{***} (3.477) [0.148, 0.553]	
Knowledge ambidexterity * Social media capability → IT infrastructure				-0.036 (-0.322) [-0.196, 0.242]	
IT infrastructure * Social media capability →				0.037	

Innovation performance				(0.215) [-0.338, 0.281]	
Social media capability → IT infrastructure				0.434*** (5.308) [0.270, 0.594]	0.538*** (6.670) [0.376, 0.695]
Innovation performance → IT infrastructure					0.045 (0.425) [-0.163, 0.251]
Innovation performance * Social media capability → IT infrastructure					0.068 (0.644) [-0.197, 0.211]
Innovation performance → Knowledge ambidexterity					0.243* (2.289) [0.002, 0.413]
Firm size → Knowledge ambidexterity					-0.015 (-0.176) [-0.182, 0.152]
Industry → Knowledge ambidexterity					0.146 (1.253) [-0.035, 0.424]
Firm age → Knowledge ambidexterity					0.047 (0.765) [-0.072, 0.173]
R^2					
Knowledge ambidexterity	0.258	0.265	0.325		0.382
Innovation performance	0.177	0.191	0.212	0.192	
IT infrastructure				0.425	0.317
SRMR value	0.007	0.020	0.059	0.073	0.123
SRMR HI_{95}	0.048	0.049	0.117	0.101	0.098
d_{ULS} value	0.001	0.019	0.410	0.639	1.385
d_{ULS} HI_{95}	0.048	0.109	1.628	1.223	0.873
d_G value	0.000	0.013	0.396	0.491	0.324
d_G HI_{95}	0.018	0.080	1.013	0.833	0.507
f^2					
IT infrastructure → Knowledge ambidexterity (H1)	0.348	0.187	0.198		0.083
Knowledge ambidexterity → Innovation performance (H2)	0.100	0.092	0.090	0.078	
IT infrastructure * Social media capability → Knowledge ambidexterity (H3a)			0.088		0.086
Knowledge ambidexterity * Social media capability → Innovation performance (H3b)			0.027		
IT infrastructure → Innovation performance	0.013	0.002	0.002	0.002	
Social media capability → Knowledge ambidexterity		0.011	0.014		0.008
Social media capability → Innovation performance		0.017	0.021	0.018	
Firm size → Innovation performance	0.001	0.001	0.001	0.001	
Industry → Innovation performance	0.060	0.054	0.047	0.049	
Firm age → Innovation performance	0.018	0.015	0.012	0.015	

Knowledge ambidexterity → IT infrastructure				0.188	
Knowledge ambidexterity * Social media capability → IT infrastructure				0.002	
IT infrastructure * Social media capability → Innovation performance				0.002	
Social media capability → IT infrastructure				0.283	0.390
Innovation performance → IT infrastructure					0.003
Innovation performance * Social media capability → IT infrastructure					0.007
Innovation performance → Knowledge ambidexterity					0.084
Firm size → Knowledge ambidexterity					0.000
Industry → Knowledge ambidexterity					0.018
Firm age → Knowledge ambidexterity					0.003

Note: *t*-values in parentheses. Bootstrapping 95% confidence interval bias corrected in square bracket (based on n = 5000 subsamples). $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ [based on $t(4999)$, one-tailed test]. $t(0.05, 4999) = 1.645$; $t(0.01, 4999) = 2.327$; $t(0.001, 4999) = 3.092$ for hypothesized relationships. $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ [based on $t(4999)$, two-tailed test]. $t(0.05, 4999) = 1.960$; $t(0.01, 4999) = 2.577$; $t(0.001, 4999) = 3.292$ for non-hypothesized relationships.

Table 8: Correlation matrix

	1	**2**	**3**	**3.1**	**3.2**	**3.3**	**4**	**5**	**6**	**7**
1. IT infrastructure	1.000									
2. Knowledge ambidexterity	0.508***	1.000								
3. Social media capability	0.557***	0.358***	1.000							
3.1. Facebook capability	0.453***	0.303***	0.891***	1.000						
3.2. Twitter capability	0.464***	0.292**	0.898***	0.751***	1.000					
3.3. Blog capability	0.536***	0.332***	0.810***	0.532***	0.597***	1.000				
4. Innovation performance	0.180*	0.335***	0.252**	0.891***	0.898***	0.209*	1.000			
5. Firm size	0.159*	0.106	0.052	0.061	0.071	0.001	-0.026	1.000		
6. Industry	0.612***	0.321***	0.272**	0.250**	0.215*	0.238**	-0.063	0.292**	1.000	
7. Firm age	-0.271**	-0.124	-0.235**	-0.212*	-0.181*	-0.216*	-0.161*	0.278**	-0.156†	1.000

5.3. Mediation analysis

Mediation analysis was performed to examine whether the indirect effects involved in the proposed model were significant. This analysis estimated and analyzed the indirect effect in the baseline model (i.e., the link between IT infrastructure and innovation performance), to explore if the indirect effect was significant (Table 9) (Benitez & Walczuch 2012; Nitzl et al. 2016; Zhao et al. 2010). The indirect effect was significant at 0.05 level while the direct effect was not significant, which suggests a full mediation of knowledge ambidexterity in the impact of IT infrastructure on innovation performance (Nitzl et al. 2016; Zhao et al. 2010). This model had very good fit (Table 7). These analyses indicate that IT infrastructure influences innovation performance through knowledge ambidexterity.

Table 9: Mediation analysis (baseline model)

Relationship	Direct effect	Indirect effect
IT infrastructure → Innovation performance	0.147 (1.304) [-0.067, 0.375]	0.169* (2.076) [0.026, 0.343]

5.4. Test of robustness

We tested the robustness of the proposed model by estimating two alternative/competing models. In the first alternative model, we assumed that knowledge ambidexterity affects the development of an IT infrastructure capability, which in turn may affect innovation performance, preserving the moderating role of social media capability. This alternative model's beta coefficients ranged from −0.036 to 0.352***, lower than those of our proposed model. Neither of the two interaction effects was significant. In the second alternative model, we considered innovation performance to affect knowledge ambidexterity through IT infrastructure, retaining the moderating role of social media capability. In this model, the beta coefficients were also lower than in our proposed model and ranged from 0.045 to 0.343***. To compare these alternative models to our proposed model, we also compared the overall fit of the baseline model and model 2, and the overall fit of the two alternative models (Braojos et al. 2015b; Henseler et al. 2014; Henseler 2015; Henseler & Dijkstra 2015). The two alternative models had higher SRMR values (0.073 and 0.123) and worse overall fit between model and data, suggesting that the proposed theory was the best and most rational explanation of our data (Benitez & Ray 2012; Braojos et al. 2015a).

5.5. Post hoc multi-group analysis: Firms with low social media capability versus firms with high social media capability

We performed a post hoc multi-group analysis to explore whether there were statistically significant differences between firms with low versus high development of social media capability relative to the effects included in the proposed model (Table 10). The calculations are based on Eq. (1) described by Sarstedt et al. (2011). We found differences between these firms in the relationship between IT infrastructure and knowledge ambidexterity, reinforcing the support for H3a. As before, the analysis did not support H3b.

Table 10: Post hoc multi-group analysis

Coefficient	Firms with low social media capability (N = 53)	Firms with high social media capability (N = 47)	Was the difference in the beta coefficient statistically significant?
IT infrastructure → Knowledge ambidexterity (H1)	0.099 (0.677) [-0.056, 0.504]	0.523*** (5.553) [0.330, 0.700]	Yes ($p < 0.01$)
Knowledge ambidexterity → Innovation performance (H2)	0.341** (2.369) [0.043, 0.671]	0.424** (2.440) [0.055, 0.753]	No (not significant)
IT infrastructure → Innovation performance	0.266† (1.643) [0.012, 0.643]	0.055 (0.245) [-0.448, 0.415]	No (not significant)
Firm size → Innovation performance (control variable)	0.193 (1.521) [-0.012, 0.494]	-0.055 (-0.420) [-0.330, 0.192]	No (not significant)
Industry → Innovation performance (control variable)	-0.351** (-2.862) [-0.593, -0.108]	-0.368 (-1.426) [-0.784, 0.225]	No (not significant)
Firm age → Innovation performance (control variable)	0.024 (0.171) [-0.283, 0.261]	-0.283* (-2.219) [-0.506, 0.004]	No (not significant)

6. Discussion and conclusions

6.1. Implications and key contributions to IS research

This research examines the impact of IT infrastructure on knowledge ambidexterity and innovation performance, and the potential moderator role of social media capability in this equation. The proposed theory was tested on a sample composed of 100 small U.S. firms, and the empirical analysis suggests that IT infrastructure enables the firm to explore new knowledge and exploit existing/new knowledge to innovate more and better. We find that IT infrastructure capability influences innovation performance through knowledge ambidexterity. The analysis also suggests that social media capability plays a moderator role in this equation: IT infrastructure and social media capabilities work together to enable knowledge ambidexterity. The empirical analysis thus supports a significant portion of our theory.

This research makes three contributions to the field of IS. First, with a few exceptions (Eseryel 2014; Joshi et al. 2010), research on the impact of IT on knowledge management and innovation activities *in the same study* is very limited. Our paper provides new evidence on how IT infrastructure enables exploration and exploitation of organizational knowledge to increase innovation performance. Unlike prior IS research, we focus on knowledge ambidexterity in small firms, drawing on prior literature on organizational ambidexterity to conceptualize knowledge ambidexterity. The ability to simultaneously pursue and balance exploration and exploitation of knowledge for operational purposes (i.e., knowledge ambidexterity) may be an even more critical capability for small firms due to their greater challenge to survive in the long run.

Second, this investigation develops the concept of social media capability for business activities (beyond marketing activities), and theorizes how this capability moderates the relationships between IT infrastructure and knowledge ambidexterity. Study of firms' use of social media for business activities is in the initial stages (Braojos et al. 2015a, 2015b). The field of IS really needs theories and empirical studies that explain whether and how social media capabilities help firms to create business value. We take a first step toward this goal by explaining and demonstrating that social media capability creates business value by amplifying the impact of leveraging technical and human IT resources to explore and exploit knowledge for operational purposes. This creation of business value is an indirect effect on firm performance by reinforcing the effect of IT infrastructure on knowledge ambidexterity to improve innovation performance.

Third, this work argues that social media constitute a complementary IT capability that complements the relationships between IT and organizational capabilities. Complementary capabilities refer to the mutual reinforcement of two activities such that the presence of one increases the value of the other (Ennen & Richter 2010). IT infrastructure and social media reinforce each other to explore and exploit organizational knowledge. The third theoretical contribution of this research is to suggest the role of social media as a complementary capability that help firms to maximize the value created from IT-enabled organizational capabilities. This argument has clear theoretical implications for developing both perspective on IT-enabled organizational capabilities (e.g., Tanriverdi 2005) and the literature on complementary capabilities (e.g., Ennen & Richter 2010). This insight suggests that the cumulative base of IT capabilities (i.e., IT infrastructure and social media) is central because these capabilities are complementary. This theoretical advance has serious implications for future IS research on IT capabilities and the intermediate organizational capabilities derived from IT. Future IS research should investigate why and how some firms develop a cumulative base of IT capabilities more quickly than others. Future research could also investigate the complementary role of social media capability in the effect of IT on the development of organizational capabilities. These are very promising avenues for future IS research.

6.2. Limitations and future research directions

This research has also some limitations. First, our findings can be only generalized to small firms in the U.S. market. We have not explored whether the proposed theoretical model is supported in samples of small firms of other markets (e.g., the European Union, Latin America, and Asia). Second, we focused on a sample composed of firms from 30 industries. Although we controlled for industry, the proposed theory may behave very differently from industry to industry. Future research might explore our theory focusing on service industries with high IT investments and/or on firms/customers that are more active in social media. Third, we analyzed three of the most popular external social media sites but did not examine the role of internal social media capabilities. Finally, two of our variables (IT infrastructure and knowledge ambidexterity) were measured through structured content analysis, a well-accepted technique for collecting secondary data but one that may have some bias. Although we measured knowledge ambidexterity based on the well-established measurement scheme of Joshi et al. (2010), and although clear discriminant validity exists between the constructs IT infrastructure and knowledge ambidexterity,[6] there may be some bias related to the "IT-enabled" emphasis of our measure of knowledge ambidexterity. Future IS research should revisit or extend our theory by designing and using survey measures of IT infrastructure and knowledge ambidexterity.

6.3. Implications for managers

The findings of this research provide two critical lessons for IT managers. First, leveraging IT technical and human resource infrastructure provides the foundation to explore and exploit market and product knowledge, ultimately to change/develop better products/processes. Leveraging IT infrastructure improves coordination within the firm and the supply chain, which in turn facilitates the firm's ability to acquire, sense, apply, and leverage knowledge for innovation benefits. Second, firms can differentiate themselves in the market if they invest and leverage Facebook, Twitter, and corporate blogs for business activities, that is, if they develop social media capability. Firms with social media capability will capture fine-grained data on the market that can be integrated into the firm's IT infrastructure to explore and

[6]The correlation between IT infrastructure and knowledge ambidexterity was moderate (0.508^{***}). Analysis of the Fornell-Larcker criteria, heterotrait-monotrait ratio of correlations, and indicator cross-loadings between IT infrastructure and knowledge ambidexterity suggested clear discriminant validity between IT infrastructure and knowledge ambidexterity (Henseler et al. 2016). Additionally, we removed the data on measures that might overlap in the measures of IT infrastructure and knowledge ambidexterity and re-estimated the baseline model, which led to almost identical results.

exploit knowledge for business benefits. In the cumulative effect of IT infrastructure and social media capabilities, the whole is greater than the sum of its parts. IT infrastructure and social media are mutually reinforcing in the exploration and exploitation of organizational knowledge. We are confident that these lessons will help IT managers to create business value from their IT/social media investment decisions.

7. References

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IT-enabled knowledge ambidexterity and innovation performance in small U.S. firms: The moderator role of social media capability

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