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Abstract

This research examines the impact of social media capability on innovation performance through knowledge ambidexterity, and the potential moderator role of business analytics talent on this equation. We test our proposed theory by performing a partial least squares path modeling on a secondary dataset on a sample composed of 100 small U.S. firms. The results of the empirical analysis suggest that social media capability enables firms to effectively balance exploration and exploitation of knowledge (i.e., knowledge ambidexterity), which in turn facilitates innovation performance. Business analytics talent plays a moderator role on these relationships.

Keywords
Social media capability, knowledge ambidexterity, innovation performance, analytics talent.

Introduction

Analytics talent is the talent of effectively applying business analytics at firm level (Ransbotham et al. 2015). Knowledge management activities have been considered a strategic issue that helps firms to survive in the long run (Lara et al. 2010). Organizational knowledge is a resource difficult to imitate, which may be a source of competitive advantage for firms (Alavi & Leidner 2001). Firms need to collect, monitor, and analyze data to achieve greater business value (He et al. 2015). Online social media platforms can be considered as facilitators of knowledge and as potential sources of innovation (Leonardi 2014). Social media platforms are considered as one of the most popular online communication tools and source of information for both individuals and firms (Chai et al. 2011). The emerging use of social media is changing the way firms communicate and interact internally and externally, thus transforming firm’s business activities (e.g., marketing, operations, human resource management) (Aral et al. 2013). However, generating and collecting data is not enough to make an efficient use of information. Monitoring, analyzing, and identifying relevant information is critical in transforming information into business gains. Ransbotham et al. (2015) suggest that using data effectively may be critical to support business activities. The process of changing data into insights to support business activities is called “business analytics” (Holsapple et al. 2014). Business analytics refers to the support of decisions making and problem resolution into the firms through two main capabilities: “speed to insight” (i.e., how fast firms can transform data into insight), and “pervasive use” (i.e., deep usage of business analytics across the firm) (Wixom et al. 2013).

Prior Information Systems (IS) research has mainly focused on analyzing the information technology (IT) impact on knowledge management and performance (e.g., Joshi et al. 2010). Few studies have examined the impact of social media on knowledge management (e.g., Beck et al. 2014; Chai et al. 2011; Hwang et al. 2015), and their effect on innovation (Leonardi 2014). Beck et al. (2014) examine whether and how the firm’s social media foster knowledge exchange among employees. Chai et al. (2011) and Hwang et al (2015) mainly focus on knowledge sharing. Chai et al. (2011) identify factors which have a positive effect on knowledge sharing of bloggers. Hwang et al. (2015) analyze how
categorical boundaries are expected to weaken, and expertise boundaries are expected to strengthen with a greater experience in the sharing of knowledge in the online community. Leonardi (2014) analyzes whether and how the firm’s social media enhance meta-knowledge and thus it fosters an improvement in innovativeness. Although some studies have focused on analyzing the user motivations to contribute in online communities (e.g., Wasko & Faraj 2005), there is a necessity to study the use of social media for supporting innovation activities at firm level (Chan et al. 2016). The relationship between social media capability and knowledge management, and its impact on innovation performance are not sufficiently explored until now, opening a promising research avenue that needs to be purposely investigated. In addition, no prior study contextualizes these relationships from an analytics talent view. Firms find difficult to efficiently use social media data for innovation activities, which suggests that the proficiency in transforming data into knowledge and leveraging this knowledge may be the base to build competitive advantages. Trying to shed light on this research problem, we attempt to answer two key research questions: 1) Does social media capability impact on innovation performance through knowledge ambidexterity? and 2) Can these relationships be strengthened when analytics talent comes into play? We theorize that the firm’s ability in using and leveraging social media for business activities (i.e., social media capability) may enable firms to balance exploration and exploitation of knowledge (i.e., knowledge ambidexterity), which in turn may improve innovation performance, and that firms with more and better analytics talent can amplify and strengthen these relationships. This is the central theoretical proposition of this manuscript.

This study investigates whether and how social media capability impacts on innovation performance through knowledge ambidexterity, and whether and how this relationship will be amplified for firms with a higher business analytics talent. We test our theory using partial least squares (PLS) path modeling, a variance-based structural equation modeling (SEM) technique, with a secondary dataset on a sample of 100 small U.S. firms.

Theory and hypotheses

Organizational Learning Framework

Organizational ambidexterity theory posits that firms are ambidextrous when they can reconcile exploration and exploitation behaviors (March 1991). Different literature streams have contributed to this topic (e.g., Technological and Innovation Management, Strategy, and Organizational Learning) (Raisch & Birkinshaw 2008). Organizational learning refers to the process in which people pursue organizational renewal through creation of knowledge, explaining, and codifying this knowledge, and sharing and transferring this knowledge within the firm to be used, and embedding them through rules, procedures, and forms (March 1991). We draw from organizational learning framework, which understands exploration and exploitation as learning activities differentiated by the level of learning (Gupta et al. 2006), to conceptualize organizational ambidexterity hence building knowledge ambidexterity concept (Benitez et al. 2016). Organizational learning defines knowledge exploration as the learning process of acquiring/creating, sharing, assimilating, and storing new knowledge, while knowledge exploitation is composed by the learning obtained from the process of reusing, reinterpreting, applying, and leveraging new/existing knowledge (Gupta et al. 2006; March 1991). Ambidextrous firms are those that efficiently balance exploration and exploitation of organizational knowledge for operational purposes (Tushman & O’Reilly 1996). Well-balancing knowledge exploration and exploitation may help firms to achieve long-term business benefits (Raisch & Birkinshaw 2008). We also use organizational learning conceptual framework to explain theoretically how knowledge ambidexterity enables innovation performance.

Social Media Capability and Knowledge Ambidexterity

Social media capability refers to the firm’s ability to purposely use and leverage external social media platforms to execute business activities (Benitez et al. 2016; Braojos et al. 2015). This study considers the most used external social media platforms (i.e., Facebook, Twitter, and corporate blogs) by the contemporary firm (Culnan et al. 2010). Knowledge ambidexterity capability is the firm’s ability to efficiently balance exploration and exploitation of organizational knowledge for operational purposes (Gupta et al. 2006; Tushman & O’Reilly 1996). Knowledge exploration refers to the learning process of experimenting with new knowledge and business opportunities by acquiring/creating, sharing, assimilating, and storing this new knowledge (March 1991). Exploitation refers to the learning process of reusing, reinterpreting, applying, and leveraging that existing/new knowledge (March 1991). Social media capability can facilitate knowledge ambidexterity of the firm. Overall, social media-enabled interaction between knowledge seekers and knowledge contributors facilitates the
development of organizational knowledge (Beck et al. 2014). There is a lack of physical and social boundaries in online environments, which facilitates accessing and transferring/sharing of new knowledge, thus facilitating the exploration of new knowledge. Firms can use social media to acquire/share large amount of knowledge from/to market (Benitez et al. 2016). For example, firms can acquire customer new knowledge (e.g., preferences and feedback on the current firm’s products, ideas for new product development) from the firm’s social media. Firms can also leverage social media to acquire knowledge on the competitor movement and activities (e.g., a supermarket that access to the key supplier base in the Twitter profile of its direct competitors). They can also use these social media platforms to share knowledge with customers (e.g., new product launching) and suppliers, thus enabling knowledge exploration.

Social media capability can also affect knowledge exploitation. Leveraging social media gives firms more flexibility to recombine, apply, and leverage new/existing knowledge (i.e., knowledge exploitation). Social media facilitate the access to repositories of solutions, in which knowledge can be easily reused and recombined reducing time and effort (Grant 1996). These repositories of knowledge allow to easily control and improve new/existing knowledge for its exploitation. For example, employees can include in corporate blogs working experience, skills, knowledge or reviews serving as a repository of new/existing knowledge, and a platform to write, link, comment other posts, making easier to interpret existing knowledge and generate new combination and interpretation of knowledge (i.e., exploitation). In summary, social media capability enables firms to acquire knowledge from customers, competitors, and suppliers. Social media capability also provides more flexibility and enhances the firm’s knowledge repository base to exploit knowledge more easily. Hence, we hypothesize that:

**Hypothesis 1 (H1): There is a positive relationship between social media capability and knowledge ambidexterity.**

**Knowledge Ambidexterity and Innovation Performance**

Innovation performance is defined as the outcomes arising from the process of changing and developing existing/new products/processes (Benitez et al. 2016; Joshi et al. 2010; Kleis et al. 2012). Knowledge ambidexterity can enable innovation performance. Firms with the ability to simultaneously combine “learning-by-experimentation” (knowledge exploration) and “localized learning” (knowledge exploitation) may maximize their innovation performance. Ambidextrous firms can understand the market, and speed up the execution of tasks, enhancing the process of new product development (Benitez et al. 2016; Lubatkin et al. 2006).

Both knowledge exploration and knowledge exploitation can improve innovation performance. Exploration brings new knowledge to the firm, increasing the number of potential innovations. These new knowledge elements, brought to the firm through exploration, increase the diversity and heterogeneity to the firm’s knowledge pool, and the possibilities of new combinations, thus improving innovation performance (Katila & Ahuja 2002). Exploration also brings to the firm a promotion of sharing and creative culture among the organization’s members, potentiating radical innovation (Lubatkin et al. 2006). Knowledge exploitation may also affect positively innovation performance. Firms can identify valuable knowledge from suppliers, employees, customers, or even competitors, and apply and leverage useful knowledge responding by performing product and process innovations. A purposely combination of market knowledge can also be leveraged to improve innovation performance (Katila & Ahuja 2002). Thus, we hypothesize:

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

**The Moderator Role of Business Analytics Talent in the Relationship between Social Media Capability and Knowledge Ambidexterity**

Business analytics talent is the firm’s talent in effectively applying business analytics by transforming data in valuable insights for supporting business activities (Ransbotham et al. 2015). Firms performing business analytics turn analytical insight into business actions (Ransbotham et al. 2015). Firms performing business analytics go from descriptive analytics to determine what occurred in the past, and what is occurring now and why, through predictive analytics to model what will occur in the future, to prescriptive analysis to develop multiple options about the future and help decide what to do (Ransbotham et al. 2015). We argue that when the firm has talent in business analytics, the relationship between social media capability and knowledge ambidexterity can be amplified, that is, business analytics talent can play a positive moderator role in this relationship.
Social media facilitate the exploration and exploitation of a vast amount of knowledge. However, business analytics talent is needed to have a good understanding, and to use this amount of knowledge efficiently. Firms with highly business analytics talent skills developed can collect, monitor, analyze, and summarize vast amount of unstructured new knowledge to quickly create meaningful knowledge (He et al. 2015), which can be easily assimilated, and stored (i.e., knowledge exploration). Firms with this ability may also extract, monitor, and analyze unstructured existing/new knowledge to be easily reused, transformed, applied, and leveraged into the firm (i.e., knowledge exploitation). In conclusion, social media data may be unstructured, subjective, and massive (Chan et al. 2016). The ideas expressed in social media can be easily misunderstood and misapplied, which exposes the firm necessity to use business analytics talent to effectively explore and exploit knowledge. In summary, business analytics talent is required by firms to assimilate, store, and leverage the useful knowledge acquired from social media. Thus, we hypothesize that:

Hypothesis 3a (H3a): Business analytics talent positively moderates the relationship between social media capability and knowledge ambidexterity.

The Moderator Role of Business Analytics Talent in the Relationship between Knowledge Ambidexterity and Innovation Performance

We also hypothesize that in presence of business analytics talent, the relationship between knowledge ambidexterity and innovation performance can be amplified, suggesting business analytics talent as positive moderator of this relationship. First, new knowledge elements, brought to the firm through exploration, increase the diversity and heterogeneity of the firm’s knowledge pool (Katila & Ahuja 2002) growing the possibilities of new combinations, thus increasing innovation performance. However, these new knowledge, often deriving from people with different backgrounds and expertise, can be difficult to translate into innovative actions. This translation may be easier for talented firms in business analytics since they can obtain a quicker and deeper understanding of how to introduce knowledge effectively in the innovation process through interpreting, assessing, filtering, manipulating, and leveraging this heterogeneous knowledge (Ransbotham et al. 2015).

Second, the process of innovation can be even more successful when the firm determines what occurred in the past, what is occurring now, and predicts what will occur in the future (i.e., analytics talent skills) reducing the uncertainties surrounding the innovation process (Ransbotham et al. 2015). Also, it is critical for the success of innovations to reduce the risk that new products will not be accepted in the market. Firms with business analytics talent can reduce this risk by better interpreting the knowledge provided by customers (Chan et al. 2016).

Third, firms with business analytics talent that use existing knowledge are more likely to benefit from a competitive advantage in innovation (Ransbotham et al. 2015). Exploiting knowledge consists in using and refining new/existing knowledge, enabling the identification and recombination of valuable knowledge to improve innovation performance (Katila & Ahuja 2002). Innovation performance may be amplified if the firm has business analytics talent, because firms with this ability reach a deeper understanding of the knowledge as it provides more transparent and accurate results, facilitating the process of combining that knowledge to improve innovation performance. Lastly, talented firms in business analytics know how to organize, standardize, and manipulate knowledge efficiently to include it into the innovation process. We therefore hypothesize the following:

Hypothesis 3b (H3b): Business analytics talent positively moderates the relationship between knowledge ambidexterity and innovation performance.

Research methodology

We test 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). This ranking is composed by the best 100 publicly recognized U.S. small firms with sales under one billion dollars (Braojos et al. 2015). The firms of our sample came from 30 industries. To check whether our sample meets the minimum required size to examine the effects included in the proposed model, prior to data collection, we performed a statistical power analysis. Assuming an anticipated medium effect size ($f^2 = 0.150$), to achieve a statistical power of 0.800, five predictors (i.e., links received by innovation performance), and alpha of 0.05, the minimum required size for our sample was 91 (Cohen 1988). As our sample size is 100 there is enough statistical power to estimate the proposed model.
Data and Measures

The data used to measure the proposed model come from nine databases. Thank to this diversity of sources, we obtained a complete secondary dataset to measure the different constructs of our model.

Social Media Capability

Social media capability is a composite second-order construct composed by three dimensions: Facebook capability, Twitter capability, and blog capability (Braojos et al. 2015; Culnan et al. 2010). Facebook capability was evaluated as a composite first-order construct through number of past and future events, experience, and updates, using information from Facebook site of the firm. Experience on Facebook was measured as the average number of months that the firm has been operating in Facebook. We measured updates by scoring with 1: Low or 5: High degree of content updating in this platform, taking into account when the firm had made the last comment on Facebook: More than one month ago/in the last month/two weeks ago/in the last week/in the last two days, getting a score of 1/2/3/4/5 respectively (Braojos et al. 2015). Twitter capability is also operationalized as a composite first-order construct with three indicators: spent time writing tweets, experience, and updates using information collected from Twitter site of the firm and Twopcharts database. The spent time writing tweets refers to the average hours that the firm has spent writing tweets. Experience and update were measured on the same way as Facebook capability (Braojos et al. 2015). Blog capability, following the same measure scheme than above, was measured through experience and updates of the firm on blogs using data collected from the firm’s blog. We measure social media capability as Braojos et al. (2015), with data collected in 2014.

Knowledge Ambidexterity

Knowledge ambidexterity is a composite first-order construct composed by two indicators: knowledge exploration and knowledge exploitation. To measure knowledge ambidexterity, we performed a structured content analysis following the Joshi et al. (2010)’s measure scheme. First, we used 18 keywords related to IT applications that support knowledge management activities (Joshi et al. 2010) to choose the firm’s news published in 2013 and 2014 from LexisNexis and Knowledge Management World databases. Then, these news were carefully read to decide whether the firm used (or not) the specific IT applications, making distinction between those IT applications that supported the acquisition, assimilation, and storage of knowledge in the firm (i.e., knowledge exploration), and those IT applications that supported the application and usage of knowledge in the firm (i.e., knowledge exploitation). Thus, knowledge exploration and exploitation were measured as the total number of news on processes of knowledge management (i.e., exploration and exploitation) enabled by IT applications.

Innovation Performance

Innovation performance was measured using information collected from the U.S. Patent and Trademark Office database related to the period from 2007 to 2014. The process of measuring innovation performance composed two phases. In the first phase, we calculated a patent quality weighting ratio (PQWR). PQWR is calculated as follows: PQWR = Number of citations that the firm’s patents of a year have received from subsequent patents within a three-year window / Number of published patents of that firm in that year. The three-year window was used to avoid vintage effects of older patents (Kleis et al. 2012). We estimated a total number of five ratios, one for each period of three years: 2007-2010, 2008-2011, 2009-2012, 2010-2013, and 2011-2014. In the second phase, we created a ranking for each industry building upon these PQWR values, having for each period as many PQWR rankings as industries in our sample. Firms belonging to each industry were ranked based on their PQWR, being better positioned those firms with higher PQWR. Based on the position of the firm in its PQWR ranking, we calculated the rate of sectoral excellence (RSE) in innovation (Benitez & Walczuch 2012; Benitez & Ray 2012). RSE considers the position of the firm in its PQWR ranking (i.e., in its industry) related to the total number of firms on that industry. RSE was calculated as follows: RSE = 1 – (Firm’s position in its industry in our PQWR ranking / Total number of firms on that industry in our PQWR ranking). The results of this calculation process were five RSEs in innovation related to 2007-2010, 2008-2011, 2009-2012, 2010-2013, and 2011-2014 for each firm. These RSEs were used as composite indicators for measuring innovation performance.

Business Analytics Talent

Business analytics talent is a first-order construct composed by one indicator. To measure business analytics talent, we performed a structured content analysis on the firm’s news published in 2013 and
2014 included in LexisNexis database. Business analytics talent was measured as the natural logarithm of the total number of business analytics talent’s features that are present in the firm. First, draw on the Ransbotham et al.’s (2015) research report, we selected a list of critical keywords related to business analytics talent. We identified on this report all the keywords closely related to the business analytics talent concept, resulting in a list of 22 critical keywords. Second, using these 22 keywords, we searched for the firm’s news published in 2013 and 2014 included in LexisNexis database. Then, these news were read to decide whether the firm had, used, or applied the specific feature of business analytics talent.

**Control Variables**

We controlled for firm size, industry, firm age, and prior innovation performance on innovation performance. It is rational to expect that bigger and more experienced firms may have more resources to invest in innovation activities. Moreover, innovation performance may be dependent of the industry where the firm operates, and prior performance can also influence subsequent performance (Benitez & Ray 2012). Firm size was measured as the natural logarithm of the average number of employees per firm in 2013 and 2014, with data collected from Forbes database (Benitez & Walczuch 2012). Industry is measured through a composite construct created by considering as reference group the dominant industry of our sample (Henseler et al. 2016). This information was collected from Forbes database and the firm website. Firm age was measured as the natural logarithm of the number of years operating of each firm in 2014 (Chen et al. 2015), with information collected from Forbes database. Prior performance was measured similarly to innovation performance, through a two-step process with information collected from the U.S. Patent and Trademark Office database. In the first step, we calculated the PQWR as follows: $\text{PQWR} = \frac{\text{Number of citations that the firm's patents of years preceding 2007 had received from subsequent patents}}{\text{Number of published patents of that firm in years preceding 2007}}$. In the second step we ranked each firm by industry according to their PQWR values. Based on the position of the firm in its PQWR ranking, we calculated the RSE in prior innovation performance for the years preceding 2007 (Benitez & Walczuch 2012; Benitez & Ray 2012). The result of this process was one RSE in prior innovation performance for each firm, which was used as a single indicator for measuring prior innovation performance.

**Empirical analysis**

The proposed theory was empirically tested using the SEM technique and the PLS method of estimation. We employed the statistical software package Advanced Analysis for Composites (ADANCO) 2.0.1 Professional for Windows (http://www.composite-modeling.com/) (Henseler & Dijkstra 2015). PLS is a well-developed method of estimation (Henseler et al. 2016), which has been largely used in the field of IS (Braojos et al. 2015; Chen et al. 2015), and its use is appropriate to test the proposed model for several reasons. First, PLS is appropriate for confirmatory research (Henseler et al. 2016). Second, all constructs of our proposed model were specified as composite, and PLS is an optimal method of estimation for composite models (Hair et al. 2012; Henseler et al. 2014; Henseler et al. 2016). Third, our proposed model has a multidimensional construct (i.e., social media capability), making it a complex model. PLS is considered a method more flexible than covariance-based method of estimations to estimate this type of models (Hair et al. 2012).

**Measurement Model Evaluation**

The constructs of our model are composite, thus we evaluate multi-collinearity, weights, loadings, and its level of significance (Cenfetelli & Bassellier 2009), by running a 5000 subsamples bootstrap analysis. To ensure that multi-collinearity is not a problem, the variance inflation factor (VIF) must be below the suggested threshold of 10 (Tanriverdi & Uysal 2015). The VIFs of the indicators/dimensions of the proposed model range from 1.112 to 6.948, suggesting that multi-collinearity is not a problem in our data (Benitez & Ray 2012). All indicators/dimensions of the model have significant weights (ranging from 0.192 to 0.659*** for indicators, and from 0.360*** to 0.424*** for dimensions) and significant loadings (ranging from 0.569*** to 0.951*** for indicators, and from 0.841*** to 0.891*** for dimensions) except for the weight of one indicator of innovation performance (i.e., RSE 2008-2011) (0.138). This composite indicator is retained because although its weight was not significant, its loading is (Cenfetelli & Bassellier 2009). We perform the two-step approach to estimate our proposed model since social media capability is a second-order construct. First, we freely correlate all the first-order constructs and dimensions of the second-order constructs to obtain the latent variables scores of the dimensions. Second, we use these latent variables scores as the manifest variable of social media capability.
We also conduct a confirmatory composite analysis to check if our structure of composite measures is correct (Henseler et al. 2014). This confirmatory composite analysis analyzes the adequacy of the composite model doing a comparison between the empirical correlation matrix and the model-implied correlation matrix. Thus, we evaluate the discrepancy between the empirical correlation matrix and the saturated model-implied correlation matrix at first, second-order, and control variable levels (Henseler 2015) by calculating the standardized root mean squared residual (SRMR), unweighted least squares (ULS) discrepancy ($d_{uls}$), and geodesic discrepancy ($d_0$) (Henseler et al. 2014). SRMR value meet the suggested threshold of being below 0.080 (Henseler et al. 2014), and all discrepancies are below the 95%-quantile of the bootstrap discrepancies (Henseler et al. 2016) for both first and second-order steps, and control variables. None of these three models should be rejected based on an alpha level of 0.05. This means that with a probability of 5% we can claim that the structure of composites of our model has the potential to explain how the corporate world functions. This issue enables us to test the proposed hypotheses. Table 1 shows the overall model fit evaluation for the confirmatory composite analysis.

### Structural Model Assessment

To test the hypothesized relationships, we perform a PLS estimation (Dijkstra & Henseler 2015) by evaluating the beta coefficients and its significance of the proposed model running a bootstrap analysis with 5000 subsamples. The $R^2$ values and the effect size ($f^2$) of the proposed relationships are also evaluated. First, we evaluate a baseline model to test $H_1$ and $H_2$. This baseline model describes the base relationships including all control variables, and excluding business analytics talent. Second, we test model 1 which includes business analytics talent in the baseline model, and finally, we test model 2 which adds the interaction terms to test $H_3a$ and $H_3b$ to the model 1. $H_1$ and $H_2$ are supported, suggesting that social media capability enables knowledge ambidexterity ($H_1$) ($\beta = 0.441$, $p_{one-tailed} < 0.001$), and knowledge ambidexterity in turn enables innovation performance ($H_2$) ($\beta = 0.326$, $p_{one-tailed} < 0.01$). $H_3a$ is also supported, which suggests that the relationship between social media capability and knowledge ambidexterity is amplified when firm has business analytics talent ($\beta = 0.223$, $p_{one-tailed} < 0.05$). Finally, we also find some support for $H_3b$, which suggests that business analytics talent amplifies in some extent the relationship between knowledge ambidexterity and innovation performance ($\beta = 0.242$, $p_{one-tailed} < 0.10$). Thus, business analytics talent plays a moderator role in these relationships. Control variables do not show any significant relationship with innovation performance in the context of our model. The $R^2$ values were 0.195 and 0.127 for baseline model, 0.282 and 0.137 for model 1, and 0.311 and 0.157 for model 2. Furthermore, the effect size analysis reports the $f^2$ values. The $f^2$ values of the key relationships of the proposed model range from 0.114 to 0.242 for baseline model, from 0.126 to 0.141 for model 1, and from 0.024 to 0.156 for model 2, which indicate from weak to medium-large effect size between the exogenous and endogenous variables of the proposed theory (Cohen 1988). Table 2 shows the results of the structural model evaluation.

The overall goodness of model fit for the structural model is evaluated, similarly to confirmatory composite analysis (Henseler et al. 2014). This measure of goodness of fit evaluates the discrepancy between the empirical correlation matrix and the estimated model-implied correlation matrix (Benitez & Ray 2012; Henseler 2015). The lower the SRMR, $d_{uls}$, and $d_0$, the better the fit between the proposed model and the data (Henseler & Dijkstra 2015). Overall, our proposed model should not be rejected based on the alpha level of 0.05 because the SRMR value (0.047) is lower than 0.080, and all discrepancies are below the 95%-quantile of the bootstrap discrepancies (Henseler et al. 2014). This means that with a probability of 5% we can claim that the proposed theory is correct to explain how the corporate and IT world function. Overall, the proposed model shows good structural model fit (Henseler & Dijkstra 2015).

### Mediation Analysis

We perform two mediation analyses to evaluate the indirect effects involved in the proposed model, and thus analyzing the mediation role of knowledge ambidexterity in the relationship between social media capability and innovation performance. To do that, we add a link from social media capability to innovation performance in (1) our baseline model (i.e., mediation baseline model), and (2) model 2

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**Table 1: Confirmatory Composite Analysis**

<table>
<thead>
<tr>
<th>Discrepancy</th>
<th>First-order level</th>
<th>Second-order level</th>
<th>Control variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Value</td>
<td>$H_{05}$</td>
<td>Conclusion</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.066</td>
<td>0.308</td>
<td>Supported</td>
</tr>
<tr>
<td>$d_{uls}$</td>
<td>0.755</td>
<td>16.262</td>
<td>Supported</td>
</tr>
<tr>
<td>$d_0$</td>
<td>0.388</td>
<td>106.115</td>
<td>Supported</td>
</tr>
</tbody>
</table>
(i.e., mediation model 2). The models with direct effects are not better models to be considered in the test of hypotheses because the models without direct effects do not have significantly worse fit than the models with direct effects (i.e., the models without direct effects fitted with the same probability than mediation models 5%, and for all discrepancies). We evaluate the indirect effects of both mediation models (0.123 and 0.093 respectively), which are significant at 0.05 level, while the direct effects are not (0.119 and 0.153 respectively) suggesting that the existence of a full mediation (Zhao et al. 2010). Thus, the effect of social media capability on innovation performance through knowledge ambidexterity is significant, suggesting that knowledge ambidexterity plays a mediator role in the relationship between social media capability and innovation performance. In these mediation models the rest of hypotheses (i.e., H1, H2, H3a, and H3b) remain supported, strengthening the results of the test of hypotheses.

**Table 2: Results of the Structural Model Evaluation**

<table>
<thead>
<tr>
<th>Beta coefficient</th>
<th>Baseline model</th>
<th>Mediation baseline model</th>
<th>Model 1</th>
<th>Mediation model 1</th>
<th>Model 2</th>
<th>Mediation model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social media capability → Knowledge ambidexterity (H1)</td>
<td>0.441***</td>
<td>0.441***</td>
<td>0.337***</td>
<td>0.337***</td>
<td>0.348***</td>
<td>0.348***</td>
</tr>
<tr>
<td>Knowledge ambidexterity → Innovation performance (H2)</td>
<td>0.326**</td>
<td>0.279**</td>
<td>0.372**</td>
<td>0.326*</td>
<td>0.321**</td>
<td>0.266*</td>
</tr>
<tr>
<td>Social media capability * Business analytics talent → Knowledge ambidexterity (H3a)</td>
<td>0.223*</td>
<td>0.223*</td>
<td>0.242*</td>
<td>0.259*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Knowledge ambidexterity * Business analytics talent → Innovation performance (H3b)</td>
<td>0.119</td>
<td>0.139</td>
<td>0.153</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social media capability → Innovation performance</td>
<td>0.313***</td>
<td>0.313***</td>
<td>0.168*</td>
<td>0.168*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Business analytics talent → Knowledge ambidexterity</td>
<td>-0.113</td>
<td>-0.134</td>
<td>-0.285*</td>
<td>-0.320**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Business analytics talent → Innovation performance</td>
<td>-0.026</td>
<td>0.049</td>
<td>0.043</td>
<td>0.039</td>
<td>0.099</td>
<td>0.099</td>
</tr>
<tr>
<td>SRMR value</td>
<td>0.054</td>
<td>0.049</td>
<td>0.043</td>
<td>0.039</td>
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</tr>
<tr>
<td>d_ULS value</td>
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<td>0.068</td>
<td>0.068</td>
<td>0.055</td>
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<tr>
<td>d_ULS H₁₀₀</td>
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<td>0.005</td>
<td>0.008</td>
<td>0.005</td>
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<tr>
<td>d_ULS H₁₀₀</td>
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<td>0.021</td>
<td>0.016</td>
<td>0.462</td>
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**Discussion and conclusions**

How to manage organizational knowledge is crucial in increasingly competitive environments (He et al. 2015). Prior literature has considered social media as a source of information and data. However, generating and collecting data is not a sufficient condition. Monitoring, analyzing, and identifying relevant information is key in transforming information into business gains (Ransbotham et al. 2015). Firms find difficult to efficiently integrate social media data into innovation activities (Chan et al. 2016). Trying to shed some light on this issue, we argue that the effective application of social media data into innovations will be achieved if firms are ambidextrous, and have business analytics talent. The aim of this study was to analyze the impact of social media capability on knowledge ambidexterity and innovation performance, and the potential moderator role of business analytics talent on this equation. To test this proposed model, we use a sample composed of 100 small U.S. firms.

How does social media capability influences innovation performance? The results of the empirical analysis show that social media capability facilitates the firm to be knowledge ambidextrous (i.e., to explore new knowledge and exploit existing/new knowledge) as social media offer new mechanisms that facilitate knowledge management (e.g., acquire and transfer new knowledge, and recombine, modify, and integrate new/existing knowledge). This knowledge ambidexterity facilitates firms to achieve greater innovation performance because exploring new knowledge increases diversity and heterogeneity to the firm’s knowledge pool, and using and refining new/existing knowledge help the firm to understand knowledge and facilitates the identification of valuable knowledge. Business analytics talent amplifies the impact of social media capability on knowledge ambidexterity, and the impact of knowledge ambidexterity on innovation performance because business analytics talent helps the firm to quickly create meaningful knowledge from unstructured new knowledge, and to better interpret the knowledge diminishing uncertainties surrounding innovation. Then, the empirical analysis supports our theory.

This study has two main contributions to the field of IS. First, there is a recognized necessity to study the use of social media for supporting firm’s innovation activities (Chan et al. 2016). We show how social media capability influences innovation performance through knowledge ambidexterity. This influence is higher if these ambidextrous firms also have business analytics talent. We consider social
media capability beyond marketing activities. We theorize and empirically analyze how social media capability helps firms to create business value (i.e., innovation performance) by enabling of knowledge ambidexterity. Second, this study develops the construct business analytics talent. This study suggests that business analytics talent is a complementary resource of social media capability and knowledge ambidexterity, since they mutually reinforce in such a way that the presence of business analytics talent increases the value of social media capability on knowledge ambidexterity, and the value of knowledge ambidexterity on innovation performance. Thus, business analytics talent helps firms to create business value from social media capability, and knowledge ambidexterity. This contribution has clear implications for the IS literature on business value of digital technologies.

The findings of this study also provide important implications for managers. First, developing social media capability helps firm to become knowledge ambidextrous to finally achieve innovation performance. Second, firms can amplify the impact of social media capability on knowledge ambidexterity, and the impact of knowledge ambidexterity on innovation performance if they recruit, develop, and retain business analytics talent. Social media capability and business analytics talent reinforce each other to obtain better knowledge ambidexterity. Knowledge ambidexterity and business analytics talent reinforce each other to create higher innovation gains. These lessons learned can be very relevant for IT and business executives, and analysts.

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References


