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Impact of Social Media on the Firm's Knowledge Exploration and Knowledge Exploitation: The Role of Business Analytics Talent

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Abstract

Social media is one of the most disruptive technologies in executing a firm's digital business transformation strategies. Does the firm's ability to use social media affect its proficiency in exploring and exploiting knowledge? What should be the role of business analytics talent in this equation? We study theoretically and empirically these cutting-edge research questions. Our proposed research model argues that social media capability enables the development of knowledge exploration and knowledge exploitation, and business analytics talent exerts a positive reinforcing role in the impact of social media on knowledge exploration. We empirically tested the proposed research model with a secondary dataset from a sample of US firms using PLS path modeling. After running a robustness test by estimating eight alternatives/competing models, the empirical analysis revealed that social media capability is positively related to knowledge exploration and knowledge exploitation, but with a stronger effect on knowledge exploration. Moreover, business analytics talent plays a positive moderator role in the relationship between social media capability and knowledge exploration. This study contributes to the IS research by (1) introducing, developing, and operationalizing the concepts of social media capability and business analytics talent; and (2) theoretically arguing and empirically showing the pivotal role of social media capability in exploring new knowledge and the complementary role of business analytics talent. Our study also provides several critical lessons learned for top executives and proposes promising future IS research avenues.

Keywords: Social Media Capability, Knowledge Exploration, Knowledge Exploitation, Business Analytics Talent, Business Value of Social Media, ADANCO

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1 Introduction

Social media represents one of the most disruptive technologies in executing a firm's digital business transformation strategies (Benitez, Ruiz et al., 2020; Wessel et al., 2021). However, our theoretical understanding of this new corporate phenomenon is in its initial stages (Benitez, Castillo et al., 2018). Social media can play a key role in collecting, monitoring, and analyzing data to generate business value (He et al., 2015), and social media platforms are considered one of the most popular online communication tools and sources of information, acting as facilitators of knowledge with potential impacts on firm performance (Benitez, Castillo et al., 2018; Chai et al., 2011; Krancher et al., 2018; Leonardi, 2014; Luo et al., 2015). For example, firms can use social media (e.g., Facebook, Twitter, corporate blogs) to build awareness about their products and initiatives and test them by collecting opinions, impressions, and ideas from customers (Dong and Wu, 2015). As an illustrative example, Lay's (a potato chip manufacturer) ran a campaign on social media (Facebook, Twitter, and Instagram) called "Do us a flavor." This campaign aimed to innovate about the next potato chip flavor by collecting ideas from customers. Four finalist flavors were sold provisionally, and customers voted in social media for the best one, with the Southern Biscuits and Gravy flavor eventually being sold. Thus, social media provides a vast amount of customer, competitor, and supplier data that can be leveraged by the firm to innovate and improve firm performance (Aral et al., 2013; Benitez, Castillo et al., 2018). Based on the organizational capabilities-based theory, this study introduces, develops, and focuses on social media capability, which refers to the firm's ability to use and leverage external social media to execute business activities. Firms with a high level of social media capability may convert social media into a golden source of data, changing how firms exchange information (Benitez, Castillo et al., 2018; French et al., 2017).

Social media may have the potential to enable firms to analyze and examine new knowledge (i.e., knowledge exploration) and recombine existing knowledge (i.e., knowledge exploitation). Knowledge exploration refers to the learning obtained from acquiring/creating, sharing, and storing new knowledge. Knowledge exploitation is the learning process of assimilating, reusing, reinterpreting, applying, and leveraging new/existing knowledge (Gupta et al., 2006; March, 1991). However, despite the suggested potential value, how firms leverage external social media to explore knowledge and exploit knowledge needs further development and empirical testing.

Generating and collecting social data (i.e., data from social media) might not be enough to use information efficiently. The value creation from social data requires knowledge understanding. Monitoring, analyzing, and identifying relevant social media-based information is critical for transforming information into business gains. Ransbotham et al. (2015) suggested that using social data effectively may be critical to support business activities. The process of changing data into valuable insights to support business activities is called "business analytics" (Chen et al., 2012; Holsapple et al., 2014; Zhang et al., forthcoming). Business analytics refers to the support of decision-making and problem resolution in firms through two main capabilities: "speed to insight" (i.e., how fast firms can transform social data into useful insights) and "pervasive use" (i.e., deep usage of business analytics across the firm) (Wixom et al., 2013). In this sense, firms face the challenge of attracting, hiring, developing, and retaining business analytics talent to transform social data into valuable insights for supporting business activities. This paper focuses on business analytics talent. As a scarce and valuable resource, business analytics talent may explain the variation in performance among contemporary firms (Edwards, 2020; Ransbotham et al., 2015). Business analytics talent is the firm's talent regarding effectively applying business analytics at the firm level by transforming data into valuable insights for supporting business activities (Ransbotham et al., 2015). Firms with business analytics talent can effectively perform business analytics to turn analytical insight into business actions. Firms effectively performing business analytics move from descriptive analytics, to determine what occurred in the past and what occurs now and why, to predictive analytics to model what will happen in the future, to prescriptive analysis to develop multiple options about the future and help determine the course of action (Ransbotham et al., 2015). Given its importance, business analytics talent is a scarce and valuable information technology (IT) resource that may help firms build IT wisdom in contemporary firms (Liu et al., 2020). It has been estimated that 2.7 million business analytics jobs will be posted in the US in 2020 alone (Fenlon & Peters, 2020).

Information systems (IS) research lacks theory building on how firms perform social media initiatives and how they may affect a firm's knowledge exploration and exploitation activities (Dong & Wu, 2015; Ngai et al., 2015). Firms may invest in managing social media effectively to acquire and exploit social data to improve their performance. This argument introduces this study's first research question: (1) Does social media capability enable knowledge exploration and knowledge exploitation? This study tries to fill this research gap and answer this question. The effect of social media capability on knowledge exploration may be stronger in firms that transform social data into new useful social knowledge through business analytics talent (Davenport et al., 2010; Ransbotham et al., 2015). This rationale motivates the second research question of this paper: (2) Can the relationship between social media capability and knowledge exploration be strengthened when business analytics talent comes into play?

We argue that social media capability can enable firms to explore and exploit knowledge, and that firms with more and better business analytics talent can amplify and strengthen the relationship between social media capability and knowledge exploration. This is the central theoretical proposition of this manuscript. We tested the proposed research model using partial least squares (PLS) path modeling with a secondary dataset on a sample of US firms. After estimating eight alternatives/competing models in the robustness check, the empirical analysis provides substantial support to our central proposition.

2 Theory and Hypotheses

2.1 Organizational Capabilities-Based Theory, IT-Enabled Organizational Capabilities, Organizational Learning Framework, and the Complementary Resource Perspective

Organizational capabilities-based theory suggests that firms design and execute IT and business strategies based on their portfolio of organizational capabilities, which explains the difference in competitiveness among firms (Grant, 1996). Organizational capabilities[1] can be classified into dynamic capabilities (a firm's proficiency in adapting its resource base in response to changes in the business environment) (Benitez, Ray et al., 2018; Teece, 2007); operational capabilities (a firm's proficiency in solving operational problems and implementing the operations strategy by using interrelated operational routines) (Benitez, Chen et al., 2018; Wu et al., 2010); and dual-purpose capabilities (organizational capabilities that are dynamic and operational capabilities because they can be controlled and exploited at both strategic/corporate and operational level) (Benitez, Ray et al., 2018; Helfat & Winter, 2011). We use the organizational capabilities-based theory to conceptualize social media capability, knowledge exploration, knowledge exploitation, business analytics talent (the key constructs of this study), and to link social media capability to knowledge exploration and knowledge exploitation.

The IT-enabled organizational capabilities perspective has emerged as a solid theoretical base in the IS literature to explain the value creation from IT by arguing that IT helps firms create business value by developing intermediate organizational/process capabilities (Lin et al., 2020; Mandrella et al., 2020; Mikalef et al., 2020; Schmiedel et al., 2020). Some of these organizational capabilities include business flexibility (Benitez, Ray et al., 2018; Benitez, Llorens et al., 2018; Chen et al., 2017), supply chain management (Ajamieh et al., 2016), corporate entrepreneurship (Chen et al., 2015), new product development (Pavlou & El Sawy, 2006), and knowledge search and relational search management (Hensen & Dong, 2020). Since social media technology is a new type of digital technology, IT-enabled organizational capabilities theory provides a useful conceptual framework to theorize that social media capability enables knowledge exploration and knowledge exploitation.

Organizational learning refers to how firms pursue organizational renewal by creating knowledge, explaining, and codifying this knowledge, and sharing and transferring this knowledge within the firm to be used and embedding it through rules and procedures (March, 1991). This study draws on the organizational learning framework, which considers knowledge exploration and exploitation as two firms' learning activities (Gupta et al., 2006). Knowledge exploration is the learning process of acquiring/creating, sharing, and storing new knowledge, while knowledge exploitation is composed of the learning obtained from the process of assimilating, reusing, reinterpreting, applying, and leveraging new/existing knowledge (Gupta et al., 2006; March, 1991). Ambidextrous firms in managing knowledge are those that efficiently achieve exploration and exploitation of knowledge simultaneously for operational purposes (Benitez, Castillo et al., 2018; Levinthal & March, 1993; Tushman and O'Reilly, 1996). Simultaneously achieving knowledge exploration and exploitation may help firms attain long-term business benefits (Raisch & Birkinshaw, 2008). Despite the importance of understanding how knowledge ambidexterity works, there is a critical difference between a firm's knowledge exploration and knowledge exploitation because they require significantly different structures, processes, strategies, capabilities, and cultural values (Dominguez & Massaroli, 2018). In this sense, knowledge exploration and knowledge exploitation may have different relationships with other variables such as social media capability, business analytics talent, and firm performance. For example, knowledge exploration is related to organic structure, flexible systems, autonomy, and improvisation, whereas knowledge exploitation is related to mechanical structure, rigid systems, control, bureaucracy, and routine (Dominguez & Massaroli, 2018). For these reasons, this study focuses on the individual impact of social media capability on knowledge exploration and knowledge exploitation instead of examining the effect of social media capability on knowledge ambidexterity. We use the organizational learning framework to conceptualize knowledge exploration and knowledge exploitation.

The complementary resource perspective is a theoretical framework that suggests that the firm's resource complementarity explains the differential effect in business benefits. Complementarity between resources/capabilities denotes the mutual reinforcing of the resources/capabilities where the presence of a resource/capability allows other resources/capabilities to exert their value (Ennen & Richter, 2010). These complementary relationships may drive the pursuit of more efficient processes, which may differ from the

[1] Organizational capabilities can be IT capabilities and business capabilities. Business capabilities refer to the non-IT capabilities of the firm. In this sense, companies can develop dynamic, operational, and dual-purpose IT and business capabilities (Benitez, Ray et al., 2018).

sum of the individual effects considered in isolation (Adegbesan, 2009; Bharadwaj et al., 2007). Our central proposition is that the positive effect of social media capability on knowledge exploration can be amplified if the firm also has business analytics talent. We use the complementary resource perspective to explain how business analytics talent complements social media capability to enable knowledge exploration.

2.2 Impact of Social Media on Organizations and Individuals, and Opportunities for IS Research

Although prior studies in this stream of IS research have highlighted the critical role of social media and provided some evidence about its impact on individuals' and organizations' knowledge sharing, there are two research opportunities in the existing literature. First, although the crucial challenge for organizations is to learn how they can develop the ability to effectively select, use, and leverage external social media among changing platforms in order to scan, learn, and internalize knowledge, it remains rather unclear how companies can develop a social media capability and create business value from this capability. Instead, prior IS research has focused on understanding the knowledge sharing behavior of employees in enterprise social media (Beck et al., 2014; Leonardi, 2014; Neely & Leonardi, 2018; Song et al., 2019), user-generated content, and customer engagement to diffuse information through social media (Bapna et al., 2019; Yang et al., 2019). Prior IS research has also focused on exploring customer behavior in social media through complaints (Gunarathne et al., 2017) service (Gunarathne et al., 2018), and the knowledge-sharing behavior of bloggers (Chai et al., 2011). Prior IS research has mainly focused on the employee, customer, and user, devoting less attention to organizations as the main level of analysis (see Table A1 in the Appendix). Despite the plausible role that the firm's proficiency in using and selecting external social media may play in exploring new knowledge and exploiting existing knowledge (Chau & Xu, 2012), this research topic is undertheorized in IS research.

Although firms' business analytics talent may perform a critical role in understanding and acquiring new knowledge from big data on customers in social media, this plausible effect is not well understood. Instead, prior IS research has primarily focused on the impact of big data analytics capability on competitive performance (Mikalef et al., 2020) and its reinforcing role in creating synergies and improving market performance (Dong & Yang, 2020). However, an overemphasis on analytics software seems to prevail, minimizing the role of people and analytics talent (Conboy et al., 2020). The goal of our research is to address these research opportunities. First, our study examines the development of social media capability and its impact on the firm's exploration and exploitation of knowledge. Second, we also examine whether and how business analytics talent reinforces the impact of social media capability on knowledge exploration. Figure 1 presents the proposed research model.

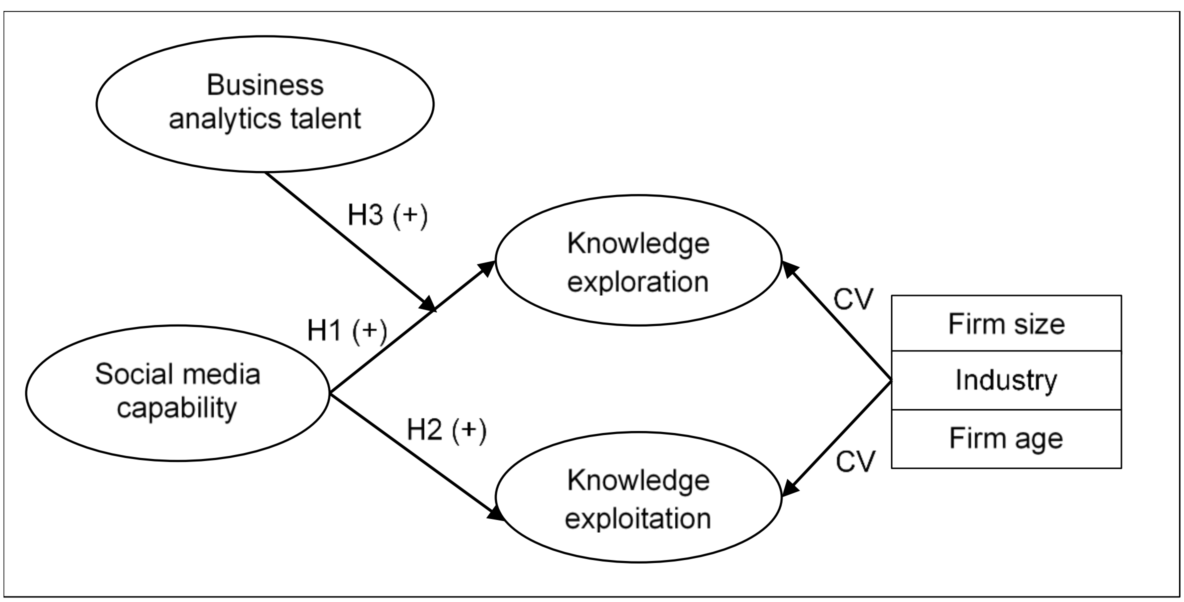

Figure 1. Proposed Research Model

2.3 Conceptualization of Key Constructs of the Study

2.3.1 Social Media Capability

Social media capability concerns the firm's ability to purposely use and leverage external social media platforms to execute business activities (Benitez, Castillo et al., 2018). This study considers the three external social media platforms (Facebook, Twitter, and corporate blogs) most used by contemporary firms (Culnan et al., 2010). In 2018 89%, 91%, and 53% of the Fortune 500 firms used Facebook, Twitter, and corporate blogs, respectively, for business activities (Barnes et al., 2019). In this sense, social media capability covers three of the most relevant external social media platforms used by firms (Braojos et al., 2015; Braojos et al., 2019). The development of social media capability is heterogeneous among companies, which suggests that companies may vary between high and low social media capabilities. Firms with highly developed social media capabilities can positively engage customers and employees to discuss their activities and cultural values and to share knowledge. Melia Hotels International (a leading hotel group worldwide) is an example of a company with high social media capabilities. Melia has leveraged social media to better manage the customer relationship/experience, improve its digital brand and web traffic, co-create knowledge, attract talent, and improve its employer branding.[2] In contrast, Molson Company (a multinational brewing company) illustrates a company with low social media capabilities. Molson Company had a static presence on Facebook in 2007 when it decided to exploit the potential of social media by launching a Facebook campaign that encouraged university students to post pictures of drinking. The company was criticized for promoting irresponsible drinking, which negatively affected its corporate reputation (Compeau & Qureshi, 2008).

Recent IS research on IT and knowledge management capabilities has operationalized the concept of IT-enabled capabilities (Joshi et al., 2010; Saldanha et al., 2020). For example, Joshi et al. (2010) conceptualized IT-enabled absorptive capacity as the IT contributions to firms' abilities to acquire, assimilate, transform, and exploit knowledge. Saldanha et al. (2020) have operationalized IT-enabled social integration capacity as the firm's IT use that fosters social capital through social interaction and connectedness. For this purpose, they also introduced several internal and external IT applications (e.g., wikis, blogs, enterprise social networking sites). We draw on this prior IS research to conceptualize social media capability. However, our social media capability concept presents unique and original characteristics concerning IT-enabled absorptive capacity and IT-enabled social integration capacity. First, social media capability refers directly and exclusively to the firm's ability to leverage external social media platforms (i.e., a specific IT). Second, in contrast to prior IS research (e.g., Andrade et al., 2018; Saldanha et al., 2020), the current study focuses not only on acquiring or recombining knowledge but on how social media capability affects firms' knowledge exploration (i.e., acquiring/creating, sharing, and storing new knowledge) and knowledge exploitation (i.e., assimilating, reusing, reinterpreting, applying, and leveraging existing knowledge).

2.3.2 Knowledge Exploration and Knowledge Exploitation

Knowledge exploration refers to the learning process of experimenting with new knowledge and business opportunities by acquiring/creating, sharing, and storing this new knowledge (March, 1991). In prior literature, two theories on organizational viability coexist to explore and exploit knowledge: as two extremes of a continuum (tradeoffs) or as two independent activities (complementary strategies) (Benitez, Castillo et al., 2018; Gupta et al., 2006). As two extremes of a continuum, exploration of new knowledge and the exploitation of existing knowledge are two extremes of the same continuum (Rosenkopf & McGrath, 2011), which invites specializing/focusing exploration or exploitation (March, 1991). A company may be situated in an intermediate position, instead of at one of the extremes, where the consideration of exploration and exploitation would be in equilibrium.

As two independent activities, knowledge exploration and exploitation are orthogonal and differentiated by the level of learning (Gupta et al., 2006; He & Wong, 2004). According to this body of literature, companies can pursue both exploration and exploitation of knowledge. Our study draws on this stream of literature to explore how social media capability affects the firm's exploration and exploitation of knowledge. Although they are complementary, given that knowledge exploration and knowledge exploitation are different, it is rational to think that they may have different relationships with other resources. Therefore, it is important and necessary to understand the different effects of other resources in these two processes. We focus on the interface between business analytics talent and the exploration and exploitation of knowledge-driven social media capability.

[2] According to Gabriel Escarrer (CEO of Melia Hotels International): "The influence of social media these days on corporate reputation and firm performance is undebatable. Being active in social media has given us the opportunity to share more and better knowledge on our company, and understanding better our customers and other stakeholders, reinforcing our relationships with them" (Hootsuite, 2020a, p. 4).

2.3.3 Business Analytics Talent

Business analytics comprise a group of people, approaches, organizational procedures, and tools used in combination that convert data into insights for problem recognition and solving within a business situation context (Holsapple et al., 2014; Trkman et al., 2010; Wixom et al., 2013). The notion of business analytics talent in this study is derived from Ransbotham et al.'s (2015) work on analytics talent, and we draw on this work to conceptualize and measure business analytics talent. Business analytics talent is a firm resource that refers to people's talent in performing business analytics (i.e., high-level analytical skills) to transform data into insights valuable for supporting business activities (Ransbotham et al., 2015). Business analytics talent is conceptually a different construct than social media capability, as some companies with high/low social media capability do not have business analytics talent because of its scarcity in the market. Our conceptualization is consistent with recent IS research that investigated big data analytics capability individually and highlighted its potential value (e.g., Mikalef et al., 2020). However, other IS scholars may be interested in examining general IT-enabled information management capability, which could potentially combine the analysis of both social media and business data analytics under the same concept and theoretical lens (e.g., Andrade & Kathuria, 2014). Our conceptualization of business analytics talent deliberately excludes business analytics talent. We propose that social media capability can enable firms to explore and exploit knowledge and that firms with more and better business analytics talent can amplify and strengthen the relationship between social media capability and firm knowledge exploration.[3]

2.4 Social Media Capability and Knowledge Exploration

Social media capability can facilitate the firm's knowledge exploration. Firms can use external social media (e.g., Facebook, Twitter, corporate blogs) to acquire new knowledge from customers, competitors, and suppliers and to create and share new knowledge with them, thus facilitating the exploration of new knowledge. Firms can use Facebook and Twitter to reach current and potential customers and interact with them to acquire customer knowledge (e.g., customer preferences and feedback on the current firm's products) (Andrade & Kathuria, 2014). These social media platforms can also be leveraged to co-develop new products with customers, (Patroni et al., forthcoming; Testa et al., 2020; Xie et al., 2016), and for knowledge sharing with customers (e.g., communication of new products), thus enabling knowledge exploration. For example, Mercadona (i.e., the leading supermarket chain in Spain) has used Twitter to acquire new customer knowledge in the form of customers' complaints about out-of-stock products in stores posted on Mercadona's Twitter site, allowing them to respond to these complaints more quickly. Mercadona has also leveraged Twitter to recognize new customer preferences (e.g., vegan products) faster than direct competitors. Thus, Mercadona is an example of a company with high-level social media capabilities that uses social media to acquire customer knowledge.

Firms can also use external social media to obtain knowledge from competitors and co-create new knowledge with their supplier network. Firms can monitor social media (Facebook, Twitter, blogs) of direct competitors to acquire knowledge on competitor moves and actions (e.g., a supermarket chain that analyzes the key supplier base of its direct competitors on Twitter) in order to design competitive strategies and actions (Andrade & Kathuria, 2014). A firm's external social media can also be used as a collaborative platform to enable knowledge exploration with suppliers by exchanging information and co-creating new products and projects. Therefore, we hypothesize:

H1: There is a positive relationship between social media capability and knowledge exploration.

2.5 Social Media Capability and Knowledge Exploitation

Social media capability can also positively influence the exploitation of existing knowledge. The firm's proficiency in selecting, using, and leveraging external social media (Facebook, Twitter, corporate blogs) may help the firm assimilate, reinterpret, reuse, and apply existing knowledge, thus increasing knowledge exploitation. The external social media can serve as customer and competitor knowledge repositories, which facilitate knowledge assimilation and reuse (Jarvenpaa & Majchrzak, 2010; Lu et al., 2015). Companies can also use external social media to develop and maintain long-term relationships with current and potential customers, collaborating and sharing knowledge with the firm to reinterpret and apply customer and product knowledge, thus enabling the exploitation of knowledge. For example, Mercadona uses Twitter to exploit existing knowledge. After its Twitter account was flooded requests for e kefir (i.e., a sour drink containing so-called gut-

[3] We check for discriminant validity between social media capability and business analytics talent by estimating the heterotrait-monotrait ratio of correlations (HTMT) (Benitez, Henseler et al., 2020). The value of the HTMT between social media capability and business analytics talent is 0.361 (lower than 0.90) and was significantly smaller than 1 (0.499), thus suggesting the existence of clear discriminant validity between these two constructs. These two constructs are both conceptually and statistically different.

friendly bacteria). Mercadona applied and leveraged this knowledge to commercialize this product in response to increasing demand in its stores, which has been acknowledged by its customers. One customer uploaded a picture of kefir with the following text: "If there is one thing that I like about Mercadona is that they always listen to the customers' suggestions." This example illustrates how firm-customer interactions in external social media (e.g., Twitter) provide Mercadona "clues" for reinterpreting and reusing existing customer and product knowledge, thus facilitating knowledge exploitation. We thus hypothesize:

H2: There is a positive relationship between social media capability and knowledge exploitation.

2.6 The Business Value of Business Analytics Talent: Business Analytics Talent as Moderator between Social Media Capability and Knowledge Exploration

We argue that when the firm has talent in business analytics, the relationship between social media capability and knowledge exploration may be amplified because business analytics talent can play a positive moderator (reinforcing) role in this relationship. Social media facilitates the exploration of a vast amount of new knowledge. However, business analytics talent must have a good understanding in order to efficiently explore this knowledge (Chau & Xu, 2012). Firms with superior business analytics talent can collect, monitor, analyze, and summarize the vast amount of unstructured new information to quickly create new insights and meaningful knowledge (He et al., 2015) that can be easily stored (i.e., knowledge exploration). Social media data are often unstructured, subjective, and massive (Chan et al., 2016). The ideas expressed in social media can be easily misunderstood and misapplied (Faraj et al., 2011), which requires firms to use analytical skills to effectively explore knowledge and convert social data into useful and understandable new knowledge. Business analytics talent is pivotal for firms seeking to create and store useful knowledge acquired from external social media. Therefore, we hypothesize:

H3: Business analytics talent positively moderates (reinforces and amplifies) the relationship between social media capability and knowledge exploration.

Table 1 presents a summary of the main arguments of the hypotheses that composes the proposed research model.

3 Research Methodology

3.1 Sample

We tested the proposed model with a sample of the 100 small firms listed in the 2013 Forbes America's Best Small Companies ranking (hereafter, the Forbes database). This ranking comprises the best 100 publicly recognized US small firms with sales under one billion dollars (Benitez, Castillo et al., 2018). The firms in our sample came from 30 industries, including consulting (18 firms), IT (16 firms), food manufacturing (7 firms), semiconductor manufacturing (6 firms), healthcare (5 firms), chemical (5 firms), and other industries (43 firms).

Prior IS research has contextualized several types of studies on the business value of IT using samples of firms included in well-known ranking lists (like the list used in this study) (e.g., Benitez, Castillo et al., 2018; Benitez & Walczuch, 2012; Joshi et al., 2010), which suggests that our decision to use the Forbes database was rational. We focused on this specific ranking list for two reasons: First, since small firms have a lower portfolio of financial resources they can use to compete in the market, leveraging their investments in social media capability and business analytics talent to manage knowledge remains central, in comparison to large firms (Benitez, Castillo et al., 2018). Second, most prior IS research on social media and business activities has focused on large firms (Luo et al., 2013; Kane, Palmer et al., 2014).

To check whether our sample met the minimum required size to examine the proposed model's effects, we performed a statistical power analysis prior to data collection. Assuming an anticipated medium effect size ($f2 = 0.150$), to achieve a statistical power of 0.800, five predictors (i.e., the number of effects received by knowledge exploration), and an alpha of 0.05, the minimum required size for our sample was 91 (Cohen, 1988). Our sample size of 100 indicates sufficient statistical power to estimate the research model.

3.2 Data and Operationalization of Variables

The data used to measure and test the proposed research model and for testing robustness came from nine databases: Facebook, Twitter, firms' blog sites, LexisNexis, Knowledge Management World, US Patent and Trademark Office, Datastream, Forbes, and firm websites. Thus, the full dataset provides an innovative and unique set of data and measures to test this study's central proposition.

Table 1. Summary of Key Theoretical Arguments of the Proposed Research Model

Hypotheses	Main theoretical arguments	Illustrative example
H1: There is a positive relationship between social media capability and knowledge exploration.	Firms can use external social media (e.g., Facebook, Twitter, corporate blogs) to acquire new knowledge from customers, competitors, and suppliers, and to create and share new knowledge with them, thus facilitating the exploration of new knowledge. For example, firms can use Facebook and Twitter to reach current and potential customers and interact with them to acquire customer knowledge (e.g., customer preferences and feedback on the current firm's products) (Andrade & Kathuria, 2014).	Nestle UK leveraged external social media (e.g., Facebook) to engage young customers and acquire new ideas to rejuvenate Kit Kat Chunky products. Customers "liked" and voted for different flavors, helping Nestle in the new product development (Mount & Garcia, 2014).
H2: There is a positive relationship between social media capability and knowledge exploitation.	The firm's proficiency in selecting, using, and leveraging external social media may facilitate firms to assimilate, reinterpret, reuse, and apply existing knowledge, thus increasing knowledge exploitation. The external social media can serve as customer and competitor knowledge repositories, which facilitate knowledge assimilation and reuse. Companies can also use external social media to develop and maintain long-term relationships with current and potential customers, which may collaborate and share knowledge with the firm to reinterpret and apply customer and product knowledge, thus enabling the exploitation of knowledge.	CaixaBank (a leading Spanish bank) has led the capability of leveraging external social media in the banking industry in Spain. CaixaBank has selected Facebook and Twitter to reuse and apply existing overall knowledge. CaixaBank has leveraged these external social media to develop and maximize customer relationships by providing viral posts on tips on recipes, health, nutrition, and sports to touch families (Gonzalez, 2020).
H3: Business analytics talent positively moderates (reinforces and amplifies) the relationship between social media capability and knowledge exploration.	Firms with superior business analytics talent can collect, monitor, analyze, and summarize the vast amount of unstructured new information to quickly create meaningful knowledge (He et al., 2015) that can be easily stored (knowledge exploration), thus amplifying the effect of social media capability on knowledge exploration.	Nestle UK used business analytics talent to develop a business data analytics capability (Mikalef et al., 2020). Nestle used business analytics talent to analyze, text mine, and data-mine customer-generated content (big data) and explore patterns of new knowledge (Mount & Garcia, 2014), thus amplifying the impact of social media on knowledge exploration.

3.2.1 Specification of the Measurement Model

A clear distinction can be made between behavioral constructs and design constructs (i.e., artifacts and emergent variables) (Benitez, Henseler et al., 2020; Henseler, 2017). While behavioral constructs are usually modeled as common factor (reflective) models, composite-formative[4] (in short, composite) constructs should be the preferred choice for modeling artifacts. These artifacts can be understood as theoretically justified constructs that consist of more elementary components (Benitez, Ray et al., 2018; Benitez, Llorens et al., 2018). They are human-made objects and concepts typically created by executives, staff, or the firm, and should be modeled as composites (Benitez, Henseler et al., 2020). The artifact serves as a proxy for the concept under investigation and can be understood as a mix of ingredients (indicators) forming the recipe (artifact) (Benitez, Ray et al., 2018; Henseler, 2015, 2017; Rueda et al., 2017). Composite modeling is how artifacts are estimated (Benitez, Henseler et al., 2020). Based on the above arguments, all research constructs were considered to be artifacts and were modeled as composites. For the sake of brevity, we refer to artifacts as composite constructs.

[4] Two types of formative measurements exist: composite-formative (artifact) and causal-formative (latent variable). The main differences between them are: (1) in composite measurement the indicators make up the construct, whereas in causal-formative measurement the indicators cause the construct, (2) high correlations among the indicators are common but not required in composite measurement, whereas correlations are not expected in causal-formative measurement, (3) the indicators of composite constructs do not involve measurement error, whereas the indicators of causal-formative constructs have measurement error, and (4) dropping an indicator alters the composite and may change its meaning, whereas dropping an indicator increases the measurement error on the causal-formative constructs (Benitez, Henseler et al., 2020; Henseler, 2017).

3.2.2 Social Media Capability

Social media capability is a composite second-order construct composed of three dimensions: Facebook capability, Twitter capability, and blog capability (Benitez, Castillo et al., 2018; Culnan et al., 2010). We used the firm's social media activities on Facebook, Twitter, and corporate blog(s) because they serve as a good proxy to evaluate social media capability (Braojos et al., 2019). It is rational to expect that firms develop a social media capability by experimenting and executing a high number of social media activities. These social media activities refer to activities performed by the firm and do not include the posts of the social media users, thus removing customer engagement metrics from social media capability measurements. The measurement and conceptualization focus on the firm's social media activities. Facebook, Twitter, and blogs are three of the most relevant external social media platforms used by companies (Benitez, Ruiz et al., 2020; Culnan et al., 2010). We measured social media capability based on the validated measure scheme from Benitez, Castillo et al. (2018) and Benitez, Ruiz et al. (2020) with data collected in 2014.

Facebook capability was evaluated as a composite first-order construct based on the following ingredients: number of events, experience, and updates, using information from the firm's Facebook site. 74% of the firms of the sample had a Facebook site; if a firm did not have a Facebook site, each of the specific ingredients of Facebook capability was coded as 0. One of these ingredients is the number of events organized on Facebook by the company. Facebook events refer to the number of past and future upcoming calendar-based occasions, such as celebrations, meetings, conferences, and showings organized by a company. From the point at which the firm's Facebook site was created until the end of the data collection period (2014), the sample firms organized 5.510 events, on average. The second ingredient of Facebook capability was the firm's experience using Facebook. Firms likely develop the ability to use and leverage Facebook through experience, trial and error, and experimentation. Facebook experience was measured as the average number of months that the firm had been operating on Facebook, from the creation of the Facebook firm's site until 2014, with information collected from the Twopcharts database. On average, the sample firms had 33.773 months of experience using Facebook. The final ingredient used to asses Facebook capability was the firm's update activity, which refers to the firm's activity in updating content on its Facebook site. The logic of this measure is that companies that frequently update their site likely have high Facebook capabilities. We measured the frequency of updates with a score of 1 (low) to 5 (high), based on when the firm made its last comment on Facebook—1: more than one month ago, 2: in the last month, 3: two weeks ago, 4: in the last week, or 5: in the last two days) (Benitez, Castillo et al., 2018). The average update activity score among the sample firms was 2.740.

Twitter capability was operationalized as a composite first-order construct using three indicators: time spent writing tweets, [5] experience, and updates using information collected from the firm's site in the Twitter and Twopcharts databases. 71% of the sample firms had a Twitter site. If a firm did not have a Twitter site, each of the specific Twitter capability ingredients was coded as 0. The spent time writing tweets refers to the average number of hours the firm spent writing tweets from the creation of the firm's Twitter site until 2014. This ingredient is likely a good indicator of Twitter capability because it measures the time a company invests in learning to use and leverage Twitter. On average, the sample firms invested 17.280 hours on Twitter. Experience and updates were measured in the same way as for Facebook capability (Braojos et al., 2019). On average, the sample firms had 35.752 months of experience using Twitter and an update activity score of 2.750.

Blog capability: Following the measurement scheme validated by Benitez, Castillo et al. (2018) and Benitez, Ruiz et al. (2020), we measured blog capability through a construct composed of firm experience and firm updates on the blog(s) using data collected from the firm's blog(s). We accessed the firm's blog by using a direct firm website link to the corporate blog used by firms to interact with their customers and other stakeholders. 35% of the firms of the sample had a corporate blog. If a firm did not have corporate blog(s), each of the specific blog capability ingredients was coded as 0. Experience and updates were measured in the same way as for Facebook capability. On average, the sample firms had 17.266 months of experience using their corporate blog and an update activity of 1.255.

3.2.3 Knowledge Exploration and Knowledge Exploitation

Knowledge exploration and knowledge exploitation are composite first-order constructs composed of five indicators. We used one indicator for each year from 2014 to 2018 as follows. To measure each indicator of knowledge exploration and exploitation, we performed a structured content analysis following Joshi et al. (2010)'s measurement scheme, which has been widely

[5] The events were a specific feature of Facebook, which precluded us from using the number of events to evaluate Twitter capability or blog capability. We measured Twitter capability and blog capability based on the validated measurement scheme of Benitez, Castillo et al. (2018) and Benitez, Ruiz et al. (2020), which includes the spent time of the firm in writing tweets as an ingredient of Twitter capability, with information collected from the Twopcharts database. The time spent by the firm writing posts on Facebook and corporate blogs was not available in the Twopcharts database, which only provided information on firms' Twitter sites.

accepted in the IS community.[6] We used secondary data based on a comprehensive examination of corporate news from various data sources. These objective data are not susceptible to common method variance or respondents' perceptions (Joshi et al., 2010). In addition to Joshi et al. (2010), other prior IS studies have suggested that these objective data and this measurement scheme are a feasible approach to measure IT applications that bolster knowledge management capabilities (e.g., Bharadwaj et al., 1999; Brynjolfsson & Hitt, 1996; Hitt & Brynjolfsson, 1996).

We measured knowledge exploration and knowledge exploitation as follows. First, we used nine keywords related to IT applications that support knowledge exploration activities and nine keywords related to IT applications that support knowledge exploitation activities to select the firm's news published in 2014, 2015, 2016, 2017, and 2018 from LexisNexis and Knowledge Management World databases.[7] The selection of IT applications that enable knowledge exploration and the list of IT applications that facilitate knowledge exploitation comes from Joshi et al. (2010). They "reviewed more than 300 articles and identified a list of IT application titles that were specifically mentioned and tied to one or more knowledge activities and capabilities in these articles." (Joshi et al., 2010, p. 482), and "created a mapping between IT technologies and knowledge capabilities based on the technology capability linkages provided in the literature." (Joshi et al., 2010, p. 482). Joshi et al. (2010) also developed six iterations until they agreed on the list of IT applications that support knowledge exploration and knowledge exploitation and engaged two external experts in IT and knowledge management "to independently assess" their coding protocol and mapping between technology categories and knowledge capabilities" (p. 484).

The news coding protocol: We followed the news coding protocol established in well-known prior studies (Andrade & Kathuria, 2014; Chi et al., 2010; Joshi et al., 2010; Saldanha et al., 2020; Zelner et al., 2009). In our study, the news coding protocol was performed by two authors and one independent external coder. Once they selected news containing our 18 keywords, the news items were carefully read to decide whether the firm used (or not) the specific IT applications, making a distinction between those that supported the acquisition and storage of knowledge in the firm (knowledge exploration), and those that supported the application and usage of knowledge in the firm (knowledge exploitation). The irrelevant news was removed. The coders fully read the entire paragraph where a keyword appeared. The disagreements between the three coders were discussed until agreement was reached. The coding protocol was then further refined based on the discussions.

As an illustrative example, in one piece of news, the coders found the following information: "The firm has migrated to a unified ERP backbone (with an expansion from nine to 12 instances)," indicating that this firm uses enterprise resource planning (ERP). Since ERP is an IT application that supports knowledge exploration activities, we coded this firm as pursuing knowledge exploration activities. In this way, knowledge exploration and knowledge exploitation were measured as the total number of news items on knowledge management (knowledge exploration and knowledge exploitation) enabled by IT applications in each year (Joshi et al., 2010). From the total number of news items identified in the databases, 10,099 news items indicated that firms used specific IT applications that support knowledge exploration and knowledge exploitation. The coders found and read 5291 news items about knowledge exploration (538 news items for 2014, 656 news items for 2015, 954 news items for 2016, 1044 news items for 2017, and 2099 news items for 2018). For knowledge exploitation, the coders found and read 4808 news items (341 news items for 2014, 353 news items for 2015, 796 news items for 2016, 1438 news items for 2017, and 1880 news items for 2018). Table 2 provides a list of these 18 keywords.

3.2.4 Business Analytics Talent

Business analytics talent is a first-order construct composed of five indicators. To measure business analytics talent, we performed structured content analysis on the firms' news published in 2014, 2015, 2016, 2017, and 2018, using the LexisNexis database.[8] Business analytics talent was measured as the total number of news items on the features of business analytics talent (i.e., distinctive attributes of business analytics talent) present in the firm. The data collection and coding protocol were developed as follows. First, based on Ransbotham et al.'s (2015) applied research report, we selected a list of critical keywords related to business analytics talent. We identified all the keywords related to the business analytics talent concept in this report, resulting in a list of 22 critical keywords.

[6] As a reference, Joshi et al.'s (2010) information systems research paper has been cited 346 times in Google Scholar.

[7] In measuring knowledge exploration and knowledge exploitation, we focused on the news published in 2014, 2015, 2016, 2017, and 2018 to smooth out good and bad firm years (Benitez, Castillo et al., 2018; Tanriverdi, 2005). We lagged the measures of knowledge exploration and knowledge exploitation because we expected a lagged effect of social media capability on the exploration and exploitation of knowledge.

[8] We focused on the news published in 2014, 2015, 2016, 2017 and 2018 to smooth out whether good and bad years for firms (Benitez Castillo et al., 2018; Tanriverdi, 2005). We lagged the measures of business analytics talent, as we expected the moderating role of business analytics talent to be lagged over time.

Table 2. List of IT Applications that Enable Knowledge Exploration and Exploitation

Construct	Reference	Keywords	Number of news items found and read in the databases
Knowledge exploration	Joshi et al. (2010)	Enterprise resource planning system (ERP) Customer relationship management system (CRM) Supply chain management system (SCM) Database Content management system Repository Information retrieval Search software Data reading system	5291 news items
Knowledge exploitation	Joshi et al. (2010)	Analytical software Business intelligence Data analytics Data mining Simulation software Decision support system Digital dashboard Online analytical processing Visualization	4808 news items

Second, using these 22 keywords related to business analytics talent, we searched for the firm's news published in 2014, 2015, 2016, 2017, and 2018, using the LexisNexis database. The news coding protocol used for business analytics talent was the same as that used to assess knowledge exploration and knowledge exploitation. The paragraphs of the news items in which one of these keywords was identified were carefully read by the coders to decide whether the firm had, used, or applied the specific feature of business analytics talent. If the firm had, used, or applied the specific feature of business analytics talent mentioned in the news, then the coders counted one per news item, resulting in the total number of news items containing these specific business analytics talent features. When one news item included more than one keyword, it was still counted as one. From the total number of news items identified from the database, 1317 news items (145 news items for 2014, 170 news items for 2015, 489 news items for 2016, 223 news items for 2017, and 290 news items for 2018) were found to have, use, or apply a specific feature of business analytics. Table 3 provides a list of these 22 keywords.

The data and measures of the key constructs included in the proposed research model include a good and objective proxy of these constructs and align well with the conceptualization of social media capability, knowledge exploration, knowledge exploitation, and business analytics talent. Table 4 summarizes the alignment between the conceptualization and the measures of the key constructs of this study.

3.2.5 Control Variables

We controlled for firm size, industry, and firm age regarding knowledge exploration and knowledge exploitation. It is rational to expect that larger and more experienced firms may have more resources to invest in firm activities involving knowledge exploration and knowledge exploitation (Benitez & Walczuch, 2012). Firm size was measured as the natural logarithm of the average number of employees per firm, with data collected from the Forbes database (Benitez, Castillo et al., 2018). Firm age was measured as the natural logarithm of the number of years that each firm was in operation (Chen et al., 2015), using information collected from the Forbes database. The exploration and exploitation of knowledge may depend on the industry where the firm operates (Benitez, Castillo et al., 2018). The industry was measured as a dummy variable (0: manufacturing firm, 1: service firm) using information collected from the Forbes database and the firm's website (Benitez, Castillo et al., 2018). Table 5 presents the descriptive statistics of the control variables.

4 Empirical Analysis and Results

The proposed research model was empirically tested using a PLS path modeling estimation. PLS is a well-developed, full-fledged structural equation modeling (SEM) method of estimation (Benitez et al., 2017; Henseler et al., 2016) that is often used in the field of IS (Benitez, Henseler et al., 2020; Chen et al., 2015; Ringle et al., 2012; Schmiedel et al., 2014).

Table 3. List of the Key Features of Business Analytics Talent

Construct	Reference	Keywords	Number of news items found and read in the database
Business analytics talent	Ransbotham et al. (2015)	Analytics skill(s) / analytical skill(s) Analytics technology / analytical technology Analytics insights / analytical insights Analytics talent / analytical talent Analytics training / analytical training Analytics worker(s) / analytical worker(s) / analytics Employee(s) / analytical employee(s) Analytics capability(s) / analytical capability(ies) Analytics tool(s) / analytical tool(s) Analytics expertise / analytical expertise Analytics resource(s) / analytical resource(s) Descriptive analytics Predictive analytics Prescriptive analytics Data worker(s) / data employee(s) Data engineer(s) Data science Data manager(s) Data skill(s) Data scientist(s) Talent strategy(s) Big data capability(s) Chief analytics officer / chief data officer	1317 news items

Table 4. Construct Conceptualization and Measures

Construct	Conceptualization	Measure	Source
Social media capability	Firm’s ability to purposely use and leverage external social media platforms to execute business activities	Second-order construct composed of Facebook capability, Twitter capability, and blog capability	Firm’s Facebook, Twitter sites, Twopcharts database, and the corporate blog
Facebook capability	Firm’s ability to use and leverage Facebook to execute business activities	Construct composed of number of events, experience, and updates	Firm’s Facebook site
Twitter capability	Firm’s ability to use and leverage Twitter to execute business activities	Construct composed of time spent posting tweets, experience, and updates	Firm’s Twitter site and Twopcharts database
Blog capability	Firm’s ability to use and leverage a blog to execute business activities	Construct composed of experience and updates	Corporate blog
Knowledge exploration	Learning process of experimenting with new knowledge and business opportunities by acquiring/creating, sharing, and storing this new knowledge	Total number of news on processes of knowledge exploration enabled by IT applications	LexisNexis database
Knowledge exploitation	Learning process of assimilating, reusing, reinterpreting, applying, and leveraging existing/new knowledge	Total number of news on processes of knowledge exploitation enabled by IT applications	LexisNexis database
Business analytics talent	Firm’s resource that refers to the talent of people on performing business analytics to be able to transform data into insights valuable for supporting business activities	Natural logarithm of the total number of news on business analytics talent’s features about the firm	LexisNexis database

Table 5. Descriptive Statistics of Control Variables

Variable	Mean	Standard deviation
Firm size	2335.187	5997.762
Industry	0.480	0.502
Firm age	34.740	21.353

Its use is appropriate to test the proposed research model for several reasons: First, PLS is appropriate for confirmatory and explanatory IS research (Benitez, Henseler et al., 2020; Braojos et al., 2020; Henseler, 2018). Second, all constructs of the proposed model were specified as artifacts and PLS is an optimal estimation method for composite models (Benitez, Henseler et al., 2020; Henseler et al., 2014; Henseler et al., 2016). Third, the proposed model has a multidimensional construct (social media capability), which increases the model's complexity. PLS method is considered to be more flexible than a covariance-based method of estimation to estimate this type of model (Hair et al., 2012).

ADANCO software package: We employed the statistical software package Advanced Analysis for Composites (ADANCO) 2.1 Professional for Windows (http://www.composite-modeling.com/) (Henseler & Dijkstra, 2015). ADANCO is a software package for composite-based SEM with a clear graphical user interface. It facilitates various second-generation statistical analyses, such as confirmatory factor analysis, confirmatory composite analysis, and SEM. Version 1.0 was introduced in 2015 by Joerg Henseler and Theo Dijkstra (Henseler & Dijkstra, 2015) to implement their recent developments, i.e., consistent PLS (Dijkstra & Henseler, 2015a, 2015b), the HTMT (Henseler et al., 2015), and the confirmatory composite analysis (Henseler et al., 2014).

> *ADANCO was programmed as a response to the criticism of existing PLS software [expressed, for instance, by Ronkko and Evermann, 2013]. Two of ADANCO's features are particularly worth mentioning: In contrast to older PLS software such as PLS-Graph and SmartPLS, the specified graphical model corresponds with the estimated statistical model. Consequently, ADANCO provides consistent estimates for the statistical model at hand. And whereas other PLS software (e.g., PLS-Graph, SmartPLS, WarpPLS, or XLSTAT-PLS) mainly aims at exploratory and predictive research, ADANCO is fully devoted to confirmatory research. As such, it puts goodness of model fit central; it encourages analysts to make use of bootstrap-based tests of goodness of model fit. Besides, it can consistently estimate both composite and common factor models. ADANCO is maintained regularly; Version 2.2 will be launched in Fall 2020. Moreover, a dedicated textbook will be published at the end of 2020 [Henseler, 2020].*[9]

We use the ADANCO software package because it provides consistent estimates, and it is appropriate for confirmatory research, such as that performed by our study.

4.1 Measurement Model Evaluation

4.1.1 Confirmatory Composite Analysis

We conducted confirmatory composite analysis to confirm that our composite measures structure was correct and supported by the data (Benitez, Henseler et al., 2020; Henseler et al., 2014). This confirmatory composite analysis analyzes the composite model's adequacy, comparing the empirical correlation matrix and the model-implied correlation matrix. It shows whether the structure of the measurements (the saturated model) is correct. We evaluated the discrepancy between the empirical correlation matrix and the saturated model-implied correlation matrix at first-order, second-order, and control variable levels (Benitez, Henseler et al., 2020; Henseler, 2015) by calculating the standardized root mean squared residual (SRMR), unweighted least squares (ULS) discrepancy (d_{ULS}), and geodesic discrepancy (d_G) (Henseler et al., 2014), three well-accepted measures of the discrepancy mentioned above (Benitez, Henseler et al., 2020; Kim et al., 2019). The structure of measurements is supported by the confirmatory composite analysis when the value of the discrepancies is lower than the 95% (or 99%) quantile of the bootstrap discrepancies. When the value of the discrepancies is lower than the 95% quantile of the bootstrap discrepancies, the structure of measurements is supported with a 5% probability (Benitez, Ray et al., 2018). When the value of the discrepancies is lower than the 99% quantile of the bootstrap discrepancies, the structure of measurements is supported with a 1%

[9] This statement comes from two interviews conducted by the second author of the current manuscript to Professor Joerg Henseler (University of Twente, The Netherlands) on May 2 and May 25, 2020. We want to thank Professor Henseler for his encouragement, help, availability, and support for the completion of these interviews and the execution of this paper.

probability (Benitez, Henseler et al., 2020). All discrepancies were below the 95% quantile of the bootstrap discrepancies (Henseler et al., 2016) for both the first- and second-order steps. None of these two models should be rejected based on an alpha level of 0.05. This means that with a probability of 5%, we can assume that the structure of measures of our model is correct. Table 6 shows the overall model fit evaluation for the confirmatory composite analysis.

4.1.2 Evaluation of the Measurement Properties

The constructs of our model (social media capability, knowledge exploration, knowledge exploitation, business analytics talent) are composite. Thus, we evaluated their multicollinearity, weights, loadings, and level of significance (Benitez, Henseler et al., 2020; Cenfetelli & Bassellier, 2009), by running a bootstrap analysis using 4,999 subsamples. To ensure that multicollinearity is not a problem, the variance inflation factor (VIF) must be below the suggested threshold of 10 (Benitez, Henseler et al., 2020; Tanriverdi & Uysal, 2015). For weights estimated by Mode A, an assessment of multicollinearity is not necessary, as they are scaled covariances and therefore ignore multicollinearity (Benitez, Henseler et al., 2020; Rigdon, 2012). Higher VIFs for knowledge exploration and knowledge exploitation (both constructs estimated by Mode A) are not a problem in the proposed model. The VIFs of the proposed model's indicators/dimensions, which are estimated by Sum Score, ranged from 1.000 to 1.470, suggesting that multicollinearity is not a problem in our data (Benitez, Ray et al., 2018). All indicators/dimensions of the model have significant weights (ranging from 0.133*** to 0.714*** for indicators, and from 0.483*** to 0.483*** for dimensions) and significant loadings (ranging from 0.508*** to 0.979*** for indicators, and from 0.520*** to 0.780*** for dimensions). We performed the two-step approach to estimate the proposed model since social media capability is a second-order construct. First, we freely correlated all the first-order constructs and dimensions of the second-order constructs to obtain the dimensions' latent variables scores. Second, we used these latent variables scores as the ingredients that compose social media capability.

We executed the following weighting scheme in our estimation. First, we started the estimation by using Mode B for all constructs. Second, we employed Mode A for those constructs with VIF values higher than 10 and/or negative weights (Benitez, Ray et al., 2018). Finally, we selected Sum Score as the preferred weighting scheme of some of the constructs, as suggested by the incremental improvements in the overall fit of the estimated model (Benitez, Henseler et al., 2020). The measurement model evaluation is presented in Table 7. The results in the confirmatory composite analysis and the evaluation of the measurement properties are good, enabling us to proceed with testing the proposed hypotheses included in the proposed research model.

4.2 Structural Model Assessment

4.2.1 Overall Model Fit Evaluation of the Estimated Model

The overall goodness of the estimated model fit was also evaluated similarly to the confirmatory composite analysis, but for the estimated model(s) (Dijkstra and Henseler, 2015a; 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 et al., 2018; Henseler et al., 2014; Henseler, 2015). The lower the SRMR, dULS, and dG, 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 all the discrepancies are below the 95% quantile of the bootstrap discrepancies (Benitez, Henseler et al., 2020; Henseler et al., 2014). These results mean that with a probability of 5%, we can claim that the proposed research model of social media and knowledge exploration and exploitation is correct for explaining how the corporate and IT world functions.

Table 6. Confirmatory Composite Analysis (saturated model[10])

Discrepancy	First-order level			Second-order level		
	Value	HI_{95}	Conclusion	Value	HI_{95}	Conclusion
SRMR	0.084	0.112	Supported	0.065	0.093	Supported
d_{ULS}	2.446	4.418	Supported	0.042	0.087	Supported
d_G	4.437	19.535	Supported	0.008	0.026	Supported

[10] "The saturated model corresponds to a model in which all constructs can freely correlate. It is related to the measurement model (Benitez, Henseler et al., 2020). The saturated model is useful to assess the quality of the measurement model, because potential model misfit can be entirely attributed to measurement model misspecification" (Henseler, 2017, p.183).

Table 7. Measurement Properties Evaluation at First- and Second-Order Level

Construct/indicator	Mean	S.D.	VIF	Weight	Loading
Social media capability (Sum Score)					
Facebook capability: Facebook activity of the firm in terms of (Sum Score)			1.470	0.483***	0.770***
Number of events	5.510	18.549	1.087	0.539***	0.703***
Experience	33.773	25.582	1.010	0.539***	0.508***
Updates	2.740	2.223	1.094	0.539***	0.644***
Twitter capability: Twitter activity of the firm in terms of (Mode A)			1.473	0.483***	0.780***
Spent time	17.280	32.149	1.307	0.262***	0.669***
Experience	35.752	27.651	2.114	0.431***	0.887***
Updates	2.750	2.284	2.254	0.483***	0.917***
Blog capability: Blog activity of the firm in terms of (Sum Score)			1.002	0.483***	0.520***
Experience	17.266	31.681	1.000	0.714***	0.701***
Updates	1.255	1.949	1.000	0.714***	0.701***
Knowledge exploration: Number of news items on processes of knowledge exploration enabled by IT applications (Mode A)					
Knowledge exploration 2014			6.623	0.255***	0.864***
Knowledge exploration 2015			3.282	0.207***	0.857***
Knowledge exploration 2016			3.541	0.235***	0.861***
Knowledge exploration 2017			14.038	0.279***	0.963***
Knowledge exploration 2018			1.564	0.206***	0.639***
Knowledge exploitation: Number of news items on processes of knowledge exploitation enabled by IT applications (Mode A)					
Knowledge exploitation 2014			5.117	0.326***	0.920***
Knowledge exploitation 2015			13.243	0.286***	0.979***
Knowledge exploitation 2016			149.310	0.164*	0.960***
Knowledge exploitation 2017			191.406	0.133***	0.950***
Knowledge exploitation 2018			101.372	0.144***	0.949***
Business analytics talent: Number of news items on analytics talent per firm (Mode A)					
Business analytics talent 2014			1.874	0.201***	0.763***
Business analytics talent 2015			9.504	0.244***	0.947***
Business analytics talent 2016			2.950	0.234***	0.829***
Business analytics talent 2017			5.411	0.261***	0.885***
Business analytics talent 2018			1.620	0.251***	0.758***
Firm size: Natural logarithm of the total number of full-time employees					
Industry: The primary industry of the firm (0: manufacturing industry, 1: service industry)					
Firm age: Natural logarithm of the number of years operating the firm					

Note: The dominant indicator approach can be executed in the ADANCO software package and refers to the indicator of a construct that is expected to correlate with the construct positively. It represents the most important ingredient of the composite construct when this information is known or assumed theoretically before the estimation (Benitez, Henseler et al., 2020). None of the constructs/indicators was considered as the dominant in our PLS estimation because we preferred to let the data and the analysis dictate the weights of the ingredients for each construct freely.

4.2.2 Test of Hypotheses

To test the hypothesized relationships, we performed a PLS estimation (Dijkstra & Henseler, 2015b) to evaluate the beta coefficients and their significance for the proposed model by running a bootstrap analysis with 4,999 subsamples. The R2 values and the effect size (f2) of the proposed relationships were also evaluated. First, we evaluated a baseline model to test H1 and H2. This baseline model describes the base relationships, including all control variables and excluding the moderator variable (business analytics talent). Second, we tested Model 1, which includes business analytics talent and adds the interaction terms (social media capability x Business analytics talent) to the baseline model to test H3. H1 and H2 are supported, suggesting that social media capability enables knowledge exploration (H1) ($\beta = 0.270$, $p < 0.001$), and knowledge exploitation (H2) ($\beta = 0.134$, $p < 0.01$). H3 is also supported, which suggests that the relationship between social media capability and knowledge exploration is amplified (positively moderated and reinforced) when the firm has business analytics talent ($\beta = 0.584$, $p < 0.01$). Thus, business analytics talent plays a reinforcing moderator role in this relationship.

Control variables did not show any significant relationship with knowledge exploration and knowledge exploitation in our model's context, except industry. The relationships between industry and knowledge exploration and industry and knowledge exploitation are positive and significant, suggesting that firms of services industries explore and exploit knowledge more than firms of manufacturing industries. The R^2 values are 0.177 and 0.060 for the baseline model and 0.750 and 0.060 for Model 1. The f^2 values of the key relationships of the proposed model range from 0.079 to 0.017 for the baseline model and from 0.017 to 0.136 for Model 1, which indicate from weak to medium-large effect sizes between the exogenous and endogenous variables of the proposed theory (Benitez, Henseler et al., 2020; Cohen, 1988). Figure 2 depicts the results of the empirical analysis. Table 8 shows the results of the test of hypotheses. Table 9 presents the correlation matrix.

4.3 Robustness Testing

We tested for the robustness of the proposed research model by estimating eight alternative/competing models. In the first alternative model, social media capability affects knowledge exploration and knowledge exploitation, and business analytics talent moderates both the relationship between social media capability and knowledge exploration and the relationship between social media capability and knowledge exploitation. The rationale for this model is that firms may additionally use analytical skills to assimilate and exploit knowledge (e.g., making predictions). In the second alternative model, social media capability affects knowledge ambidexterity (i.e., a composite first-order construct composed of two indicators: knowledge exploration and knowledge exploitation), and business analytics talent moderates the relationship between social media capability and knowledge ambidexterity. The rationale for this research model is to examine the effects of social media and business analytics talent in the simultaneous pursuit of exploration and exploitation (i.e., knowledge ambidexterity).

In the third alternative model, social media capability affects knowledge exploration and knowledge exploitation, which affect firm performance, retaining the moderating role of business analytics talent in the relationship between social media capability and knowledge exploration. The rationale for this research model is to examine the final and full effects on firm performance. In the fourth alternative model, social media capability enables knowledge exploration and knowledge exploitation, and knowledge exploration facilitates knowledge exploitation, preserving the moderating role of business analytics talent. Benitez, Llorens et al. (2018) found that firms explore business opportunities first and then exploit opportunities through operational capabilities (the company's heart and core). Drawing on Benitez, Llorens et al. (2018), the rationale for this fourth alternative research model is that knowledge exploration may precede knowledge exploitation. In the fifth alternative model, social media capability enables knowledge exploration and knowledge exploitation, knowledge exploration facilitates knowledge exploitation, and business analytics talent moderates both the relationship between social media capability and knowledge exploration and the relationship between knowledge exploration and knowledge exploitation.

In the sixth alternative model, we measure Facebook capability, Twitter capability, and blog capability with experience and updates, that is, with homogeneous measurements, but every other model specification stays the same. The seventh alternative model controls for advertising spending on knowledge exploration and knowledge exploitation. The rationale is that the development of social media capability and its effects on knowledge exploration and knowledge exploitation may be affected by the firm's marketing activities. Finally, the eighth alternative model combines the model specifications of the second and seventh alternative models but estimates knowledge ambidexterity by multiplying knowledge exploration and knowledge exploitation. The next section presents the results of the estimation of these eight alternative models.

Table 8. Results of Hypotheses Testing

Beta coefficient	Baseline model		Model 1	
Social media capability → Knowledge exploration (H1)	0.270^{***} (4.345) [0.173, 0.396]		0.204^{*} (1.953) [0.065, 0.455]	
Social media capability → Knowledge exploitation (H2)	0.134^{**} (2.334) [0.070, 0.313]		0.134^{**} (2.334) [0.070, 0.313]	
Social media capability * Business analytics talent → Knowledge exploration (H3)			0.584^{**} (2.678) [0.196, 0.916]	
Business analytics talent → Knowledge exploration			0.209 (0.911) [-0.206, 0.562]	
Firm size → Knowledge exploration (control variable)	0.034 (0.520) [-0.100, 0.159]		-0.042 (-0.883) [-0.160, 0.029]	
Firm size → Knowledge exploitation (control variable)	0.054 (0.717) [-0.039, 0.260]		0.054 (0.717) [-0.039, 0.260]	
Industry → Knowledge exploration (control variable)	0.224^{***} (4.158) [0.126, 0.341]		0.102^{*} (1.868) [0.004, 0.219]	
Industry → Knowledge exploitation (control variable)	0.153^{***} (3.610) [0.099, 0.264]		0.153^{***} (3.610) [0.099, 0.264]	
Firm age → Knowledge exploration (control variable)	-0.058 (-0.863) [-0.185, 0.070]		-0.025 (-0.620) [-0.090, 0.071]	
Firm age → Knowledge exploitation (control variable)	0.055 (0.493) [-0.205, 0.194]		0.055 (0.477) [-0.205, 0.194]	
Endogenous variables	**R^2**	**Adjusted R^2**	**R^2**	**Adjusted R^2**
Knowledge exploration	0.177	0.142	0.750	0.734
Knowledge exploitation	0.060	0.021	0.060	0.021
Discrepancy	**Value**	**HI_{95}**	**Value**	**HI_{95}**
SRMR	0.027	0.099	0.045	0.143
d_{ULS}	0.026	0.356	0.160	1.586
d_G	0.008	0.288	0.593	6.253
f^2				
Social media capability → Knowledge exploration (H1)	0.079		0.105	
Social media capability → Knowledge exploitation (H2)	0.017		0.017	
Social media capability x Business analytics talent → Knowledge exploration (H3)			0.136	
Business analytics talent → Knowledge exploration			0.016	
Firm size → Knowledge exploration (control variable)	0.001		0.006	
Firm size → Knowledge exploitation (control variable)	0.003		0.003	
Industry → Knowledge exploration (control variable)	0.049		0.032	
Industry → Knowledge exploitation (control variable)	0.020		0.020	
Firm age → Knowledge exploration (control variable)	0.003		0.002	
Firm age → Knowledge exploitation (control variable)	0.003		0.003	

Note: t-values in parentheses. Bootstrapping 95% confidence interval bias corrected in square bracket (based on n = 4999 subsamples). †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (based on $t(4,998)$), one-tailed test).

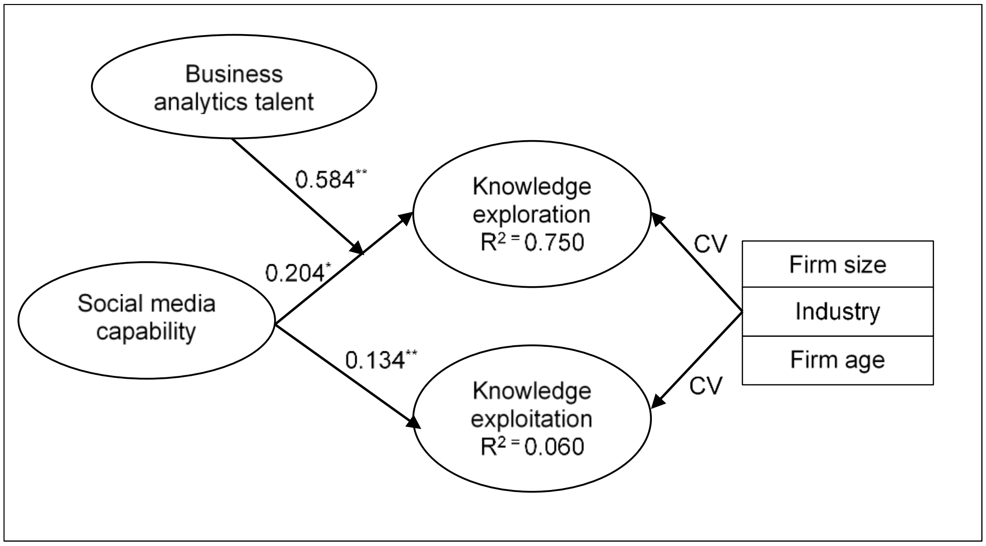

Figure 2. Results of the Empirical Analysis

Table 9. Correlation Matrix

	1	1.1	1.2	1.3	2	3	4	5	6	7
1. Social media capability	1.000									
1.1. Facebook capability	0.770	1.000								
1.2. Twitter capability	0.780	0.566	1.000							
1.3. Blog capability	0.520	0.028	0.049	1.000						
2. Knowledge exploration	0.289	0.303	0.311	-0.017	1.000					
3. Knowledge exploitation	0.152	0.088	0.203	0.024	0.152	1.000				
4. Business analytics talent	0.257	0.250	0.278	0.004	0.835	0.280	1.000			
5. Firm size	0.067	0.054	0.074	0.011	0.103	0.123	0.177	1.000		
6. Industry	0.207	0.273	0.229	-0.074	0.319	0.198	0.296	0.292	1.000	
7. Firm age	-0.147	-0.196	-0.178	0.069	-0.140	0.018	-0.086	-0.156	0.278	1.000

4.3.1 Business Analytics Talent as Moderator between Social Media Capability and Knowledge Exploitation

In the first alternative model, we assume that social media capability affects knowledge exploration and knowledge exploitation, and that business analytics talent moderates both relationships (i.e., social media capability affects knowledge exploration and social media capability affects knowledge exploitation). The rationale for testing this model is that business analytics talent may enable firms to extract, monitor, and analyze unstructured existing/new knowledge to be reused, transformed, applied, and leveraged in the firm, which may reinforce the effect of social media capability on knowledge exploitation. This first alternative model yielded results similar to those obtained in the proposed model, but the moderating effect of business analytics talent in the relationship between social media capability and knowledge exploitation was not significant ($\beta = -0.476$). Table 10 shows the results of this robustness model, indicating that business analytics talent does not amplify the effect of social media capability on knowledge exploitation.

Table 10. Robustness Test Results: Moderator Role of Business Analytics Talent in the Relationship between Social Media Capability and Knowledge Exploitation

Beta coefficient	Baseline model		Model 1	
Social media capability → Knowledge exploration (H1)	0.270^{***} (4.345) [0.173, 0.396]		0.240^{*} (1.926) [0.021, 0.508]	
Social media capability → Knowledge exploitation (H2)	0.134^{**} (2.334) [0.070, 0.313]		-0.025 (-0.163) [-0.247, 0.394]	
Social media capability * Business analytics talent → Knowledge exploration (H3a)			0.673^{*} (1.897) [-0.601, 0.952]	
Social media capability * Business analytics talent → Knowledge exploitation (H3b)			-0.476 (-0.670) [-1.411, 1.438]	
Business analytics talent → Knowledge exploration			0.111 (0.292) [-0.288, 1.116]	
Business analytics talent → Knowledge exploitation			0.708 (1.070) [-0.901, 1.881]	
Firm size → Knowledge exploration (control variable)	0.034 (0.520) [-0.100, 0.159]		-0.040 (-0.849) [-0.160, 0.028]	
Firm size → Knowledge exploitation (control variable)	0.054 (0.717) [-0.039, 0.260]		0.016 (0.262) [-0.088, 0.167]	
Industry → Knowledge exploration (control variable)	0.224^{***} (4.158) [0.126, 0.341]		0.101^{*} (1.813) [-0.004, 0.216]	
Industry → Knowledge exploitation (control variable)	0.153^{***} (3.610) [0.099, 0.264]		$0.089^{\dagger}$ (1.542) [-0.046, 0.191]	
Firm age → Knowledge exploration (control variable)	-0.058 (-0.863) [-0.185, 0.070]		-0.023 (-0.552) [-0.092, 0.073]	
Firm age → Knowledge exploitation (control variable)	0.055 (-0.863) [-0.205, 0.194]		0.061 (0.632) [-0.142, 0.207]	
Endogenous variables	**R^2**	**Adjusted R^2**	**R^2**	**Adjusted R^2**
Knowledge exploration	0.177	0.142	0.750	0.734
Knowledge exploitation	0.060	0.021	0.120	0.063
Discrepancy	**Value**	**HI_{95}**	**Value**	**HI_{95}**
SRMR	0.027	0.099	0.037	0.122
d_{ULS}	0.026	0.356	0.108	1.151
d_G	0.008	0.288	0.455	6.266

4.3.2 The Relationship between Social Media Capability and Knowledge Ambidexterity

In the second alternative model, we propose that social media capability affects knowledge ambidexterity, and business analytics talent moderates the relationship between social media capability and knowledge ambidexterity. Thus, we examine the potential enabling role of social media capability on knowledge ambidexterity and the potential amplifying role of business analytics talent in this relationship. We operationalized knowledge ambidexterity as a composite first-order construct composed of two indicators: knowledge exploration and knowledge exploitation. Results show that the link between social media capability and knowledge ambidexterity in the baseline model (i.e., a model describing the base relationship between social media capability and knowledge ambidexterity, including all control variables and excluding business analytics talent) was positive and significant ($\beta = 0.285$, $p < 0.001$). Moreover, the moderating effect of business analytics talent in the relationship between social media capability and knowledge ambidexterity was positive and significant ($\beta = 0.524$, $p < 0.05$). The results of this empirical analysis suggest that firms effectively using social media simultaneously explore and exploit knowledge, and that business analytics talent amplifies the impact of social media capability on knowledge ambidexterity. Table 11 presents the results of this alternative model.

4.3.3 The Relationship between Knowledge Exploration and Knowledge Exploitation and Firm Performance

In the third alternative model, we propose that social media capability affects knowledge exploration and knowledge exploitation, which affects firm performance, preserving the moderating role of business analytics talent in the relationship between social media capability and knowledge exploration. Prior research has suggested a firm's knowledge management activities as a source of superior firm performance (Lee et al., 2020; Tanriverdi, 2005). The ability to bring new knowledge from social media to the firm (i.e., knowledge exploration) increases the diversity and heterogeneity of the firm's knowledge pool and the possibilities of new knowledge combinations, thus improving firm performance such as innovation performance (Katila & Ahuja, 2002). When the discovered knowledge is exploited and leveraged, the firm creates business value (e.g., converting new knowledge in product and process innovation) (Benitez, Ray et al., 2018; Benitez, Llorens et al., 2018, Lubatkin et al., 2006). In this alternative model, we operationalized firm performance in terms of financial performance, marketing performance, and innovation performance. To measure financial performance and marketing performance, we collected data from the Datastream database from 2014 to 2018. To measure innovation performance, we collected data from the US Patent and Trademark Office in the same period. The links between knowledge exploration and firm performance ($\beta = 0.145$, $p < 0.05$), and knowledge exploitation and firm performance ($\beta = 0.256$, $p < 0.001$) are positive and significant. Therefore, the empirical analysis results for this alternative model suggest that firms effectively use social media to explore and exploit knowledge. The firm's proficiency in exploring new knowledge and exploiting existing/new knowledge enables the firm to improve performance. Since the analysis of the effects of knowledge exploration and knowledge exploitation on firm performance goes beyond the goal of this paper and has already been explored in prior IS research (e.g., Kathuria et al. 2016), we kept this model only in the robustness check. Table 12 shows the results of this alternative model.

4.3.4 The Relationship between Knowledge Exploration and Knowledge Exploitation

In the fourth alternative model, we assume that social media capability affects knowledge exploration and knowledge exploitation, and knowledge exploration affects knowledge exploitation preserving the moderating role of business analytics talent in the relationship between social media capability and knowledge exploration. The theoretical argument to test this model is based on prior studies, suggesting that exploration enables exploitation in different contexts. Evidence supports the effect of exploration on exploitation in the context of business opportunities (Benitez, Llorens et al., 2018) and the context of mergers and acquisitions (Benitez, Ray et al., 2018). However, in the specific context of knowledge exploration and knowledge exploitation, in our sample of small US firms, we did not find a significant relationship between knowledge exploration and knowledge exploitation ($\beta = 0.071$). Future research should explore the relationship between knowledge exploration and knowledge exploitation in firms of different sizes and geographic contexts.

4.3.5 Business Analytics Talent as Moderator between Knowledge Exploration and Knowledge Exploitation

In the fifth alternative model, we assume that social media capability affects knowledge exploration and knowledge exploitation, and knowledge exploration affects knowledge exploitation, keeping the moderator role of business analytics talent in the relationship between social media capability and knowledge exploration and adding a moderator role of business analytics talent in the relationship between knowledge exploration and knowledge exploitation.

Table 11. Robustness Test Results: Relationship between Social Media Capability and Knowledge Ambidexterity

Beta coefficient	**Baseline model**		**Model 1**	
Social media capability → Knowledge ambidexterity	0.285^{***} (4.439) [0.184, 0.420]		0.212^{*} (2.114) [0.045, 0.045]	
Social media capability x Business analytics talent → Knowledge ambidexterity			0.524^{*} (2.022) [-0.026, 0.845]	
Business analytics talent → Knowledge ambidexterity			0.270 (0.949) [-0.113, 0.890]	
Firm size → Knowledge ambidexterity (control variable)	0.050 (0.654) [-0.088, 0.217]		-0.036 (-0.788) [-0.144, 0.037]	
Industry → Knowledge ambidexterity (control variable)	0.252^{***} (4.507) [0.146, 0.366]		0.112^{*} (2.014) [-0.025, 0.203]	
Firm age → Knowledge ambidexterity (control variable)	-0.030 (-0.396) [-0.185, 0.112]		-0.011 (-0.269) [-0.069, 0.101]	
Endogenous variables	**R^2**	**Adjusted R^2**	**R^2**	**Adjusted R^2**
Knowledge ambidexterity	0.204	0.170	0.765	0.750
Discrepancy	**Value**	**HI_{95}**	**Value**	**HI_{95}**
SRMR	0.031	0.089	0.043	0.126
d_{ULS}	0.033	0.282	0.142	1.229
d_G	0.009	0.100	0.493	6.174

Table 12. Robustness Test Results: The Effect of Knowledge Exploration and Exploitation on Firm Performance

Beta coefficient	**Baseline model**	**Model 1**
Social media capability → Knowledge exploration (H1)	0.270^{***} (4.343) [0.173, 0.396]	0.204^{*} (1.957) [0.065, 0.457]
Social media capability → Knowledge exploitation (H2)	0.133^{**} (2.323) [0.070, 0.315]	0.133^{**} (2.323) [0.070, 0.315]
Social media capability * Business analytics talent → Knowledge exploration (H3)		0.584^{**} (2.684) [0.194, 0.914]
Knowledge exploration → Firm performance	0.145^{*} (1.860) [-0.010, 0.284]	0.145^{*} (1.860) [-0.010, 0.284]
Knowledge exploitation → Firm performance	0.266^{***} (2.548) [0.039, 0.466]	0.256^{***} (2.548) [0.039, 0.466]
Business analytics talent → Knowledge exploration		0.207 (0.905) [-0.206, 0.561]
Firm size → Knowledge exploration (control variable)	0.034 (0.512) [-0.101, 0.159]	-0.043 (-0.888) [-0.160, 0.028]
Firm size → Knowledge exploitation (control variable)	0.053 (0.701) [-0.039, 0.262]	0.053 (0.701) [-0.039, 0.262]
Firm size → Firm performance (control variable)	0.332^{**} (3.585)	0.332^{***} (3.585)

	[0.149, 0.511]		[0.149, 0.511]	
Industry → Knowledge exploration (control variable)	0.224*** (4.158) [0.126, 0.341]		0.102* (1.871) [0.004, 0.219]	
Industry → Knowledge exploitation (control variable)	0.152*** (3.577) [0.099, 0.265]		0.152*** (3.577) [0.099, 0.265]	
Firm age → Knowledge exploration (control variable)	-0.058 (-0.863) [-0.186, 0.070]		-0.025 (-0.620) [-0.090, 0.071]	
Firm age → Knowledge exploitation (control variable)	0.056 (0.490) [-0.205, 0.195]		0.056 (0.490) [-0.205, 0.195]	
Industry → Firm performance (control variable)	-0.060 (-0.566) [-0.287, 0.130]		-0.060 (-0.566) [-0.287, 0.130]	
Firm age → Firm performance (control variable)	-0.133* (-1.611) [-0.286, 0.038]		-0.133* (-1.611) [-0.286, 0.038]	
Endogenous variables	**R^2**	**Adjusted R^2**	**R^2**	**Adjusted R^2**
Knowledge exploration	0.177	0.142	0.748	0.732
Knowledge exploitation	0.060	0.020	0.060	0.020
Firm performance	0.214	0.172	0.214	0.172
Discrepancy	**Value**	**HI_{95}**	**Value**	**HI_{95}**
SRMR	0.031	0.099	0.047	0.137
d_{ULS}	0.042	0.439	0.198	1.710
d_G	0.011	0.296	0.605	6.404

The rationale for testing this model is that business analytics talent can be the pivotal complementary resource to move explored social media-enabled knowledge into exploited knowledge. This additional analysis might explain the lack of support for the effect of knowledge exploration on knowledge exploitation in the fourth alternative model.[11] However, in this alternative model, the moderating effect of business analytics talent in the relationship between knowledge exploration and knowledge exploitation was not significant (β = -0.413). Future IS research should explore the relationship between knowledge exploration and knowledge exploitation and the potential moderator role of business analytics talent in firms of different sizes (e.g., small European firms) and geographic contexts (e.g., Asian companies).

4.3.6 Model with Homogeneous Measurements for Facebook Capability, Twitter Capability, and Blog Capability

We are confident in the alignment between the conceptualization and measurement of social media capability, and the confirmatory composite analysis has also supported our measurements. However, there are small differences in the ingredients of Facebook capability, Twitter capability, and blog capability that can be explained by the nature of the social media platforms (e.g., number of events in Facebook capability) and the data availability (e.g., time spent writing tweets as a measure of Twitter capability). The two common and homogeneous measurements of the three social media capabilities are experience and updates. In the sixth alternative model, we measure Facebook capability, Twitter capability, and blog capability using experience and updates only—that is, using homogeneous measurements—with every other model specification kept the same. Table 13 presents the results of this alternative model. The results of this model are consistent with our hypothesis testing results and indicate that the variation in the ingredients of Facebook capability, Twitter capability, and blog capability does not affect the findings of this study.

4.3.7 Model Controlling for Firm's Advertising Spending on Knowledge Exploration and Knowledge Exploitation

The seventh alternative model controls for firms' advertising spending on knowledge exploration and knowledge exploitation. The rationale is that the development of social media capability and its effects on

[11] We very much appreciate the suggestion of one anonymous reviewer on this issue.

knowledge exploration and knowledge exploitation may be affected by a firm's marketing activities and resources. We measure the firm's advertising spending as the firm's average annual advertising spending for the years 2014-2018, using information from the ORBIS database. Table 14 presents the results of this model, which suggest that, after controlling for the firm's advertising spending, our study's findings are consistent and robust.

4.3.8 Model Controlling for Firm's Advertising Spending on Knowledge Ambidexterity

The eighth alternative model combines the model specifications of the second and seventh alternative models but estimates knowledge ambidexterity by multiplying knowledge exploration and knowledge exploitation. This ingredient specification is another alternative way to measure ambidexterity, as suggested by prior organizational ambidexterity literature. The firm's advertising spending (control variable) was measured as in the seventh alternative model. Table 15 presents the results of the eighth alternative model. This additional analysis suggests that the construct specification of knowledge ambidexterity after controlling for advertising spending does not affect the findings of this study.

Table 13. Robustness Test Results: Facebook Capability, Twitter Capability, and Blog Capability Measured with Experience and Updates

Beta coefficient	Baseline model		Model 1	
Social media capability → Knowledge exploration (H1)	0.292*** (5.037) [0.190, 0.416]		0.298** (2.543) [0.024, 0.495]	
Social media capability → Knowledge exploitation (H2)	0.154* (1.928) [0.124, 0.436]		0.154* (1.928) [0.124, 0.436]	
Social media capability * Business analytics talent → Knowledge exploration (H3)			0.832** (2.268) [-0.150, 1.211]	
Business analytics talent → Knowledge exploration			-0.077 (-0.208) [-0.528, 0.916]	
Firm size → Knowledge exploration (control variable)	0.113† (1.318) [-0.046, 0.294]		0.047 (0.687) [-0.090, 0.177]	
Firm size → Knowledge exploitation (control variable)	0.033 (0.308) [-0.055, 0.356]		0.033 (0.308) [-0.055, 0.356]	
Industry → Knowledge exploration (control variable)	0.194*** (3.614) [0.111, 0.313]		0.092* (1.975) [0.001, 0.183]	
Industry → Knowledge exploitation (control variable)	0.111* (1.953) [0.095, 0.304]		0.111* (1.953) [0.066, 0.284]	
Firm age → Knowledge exploration (control variable)	-0.073* (-1.188) [-0.190, 0.051]		-0.042 (-1.158) [-0.112, 0.033]	
Firm age → Knowledge exploitation (control variable)	0.103 (0.955) [-0.162, 0.227]		0.103 (0.955) [-0.162, 0.227]	
Endogenous variables	**R^2**	**Adjusted R^2**	**R^2**	**Adjusted R^2**
Knowledge exploration	0.198	0.165	0.756	0.740
Knowledge exploitation	0.051	0.011	0.051	0.011
Discrepancy	**Value**	**HI_{95}**	**Value**	**HI_{95}**
SRMR	0.022	0.093	0.041	0.138
d_{ULS}	0.017	0.311	0.130	1.480
d_G	0.008	0.186	0.562	1.627

Table 14. Robustness Test Results: Model Controlling for Firm's Advertising Spending

Beta coefficient	Baseline model		Model 1	
Social media capability → Knowledge exploration (H1)	0.270^{***} (4.300) [0.170, 0.398]		0.204^{*} (1.944) [0.065, 0.314]	
Social media capability → Knowledge exploitation (H2)	0.134^{**} (2.300) [0.065, 0.314]		0.134^{**} (2.300) [0.066, 0.314]	
Social media capability * Business analytics talent → Knowledge exploration (H3)			0.584^{**} (2.666) [0.193, 0.918]	
Business analytics talent → Knowledge exploration			0.209 (0.908) [-0.205, 0.565]	
Firm size → Knowledge exploration (control variable)	0.033 (0.464) [-0.107, 0.168]		-0.042 (-0.817) [-0.170, 0.033]	
Firm size → Knowledge exploitation (control variable)	0.054 (0.702) [-0.036, 0.274]		0.054 (0.702) [-0.036, 0.274]	
Industry → Knowledge exploration (control variable)	0.223^{***} (4.168) [0.128, 0.341]		0.102^{*} (1.908) [0.007, 0.217]	
Industry → Knowledge exploitation (control variable)	0.153^{***} (3.558) [0.076, 0.269]		0.153^{***} (3.558) [0.101, 0.269]	
Firm age → Knowledge exploration (control variable)	-0.058 (-0.862) [-0.186, 0.074]		-0.025 (-0.607) [-0.091, 0.073]	
Firm age → Knowledge exploitation (control variable)	0.055 (0.470) [-0.205, 0.202]		0.055 (0.470) [-0.205, 0.202]	
Advertising spending → Knowledge exploitation (control variable)	-0.010 (-0.226) [-0.053, 0.113]		0.001 (0.025) [-0.052, 0.052]	
Advertising spending → Knowledge exploitation (control variable)	0.001 (0.012) [-0.039, 0.143]		0.001 (0.048) [-0.039, 0.143]	
Endogenous variables	**R^2**	**Adjusted R^2**	**R^2**	**Adjusted R^2**
Knowledge exploration	0.177	0.133	0.750	0.731
Knowledge exploitation	0.060	0.010	0.060	0.010
Discrepancy	**Value**	**HI_{95}**	**Value**	**HI_{95}**
SRMR	0.025	0.170	0.042	0.138
d_{ULS}	0.028	0.515	0.163	1.738
d_G	0.009	0.700	0.595	6.399

Note: The analysis of this table measures the firm's advertising spending as the average annual advertising spending for the years 2014-2018. We repeated the analysis by measuring advertising spending only for 2013, only for 2014, and estimating an average for 2013-2017. All the results of these alternative measures for the firm's advertising spending yield similar results.

Table 15. Robustness Test Resluts: Model Controlling for Firm's Advertising Spending on Knowledge Ambidexterity (estimated as multiplying knowledge exploration and knowledge exploitation)

Beta coefficient	**Baseline model with advertising spending**		**Model 1 with advertising spending**	
Social media capability → Knowledge ambidexterity	0.190* (1.896) [0.080, 0.445]		0.230* (2.196) [0.025, 0.457]	
Social media capability * Business analytics talent → Knowledge ambidexterity			0.397* (2.003) [0.052, 0.851]	
Business analytics talent → Knowledge ambidexterity			-0.022 (-0.099) [-0.266, 0.615]	
Firm size → Knowledge ambidexterity (control variable)	0.223† (1.483) [-0.069, 0.461]		0.188† (1.261) [-0.113, 0.392]	
Industry → Knowledge ambidexterity (control variable)	0.137* (2.065) [0.043, 0.298]		0.069 (1.198) [-0.043, 0.190]	
Firm age → Knowledge ambidexterity (control variable)	-0.032 (-0.489) [-0.153, 0.107]		-0.013 (-0.264) [-0.094, 0.109]	
Advertising spending → Knowledge ambidexterity (control variable)	0.191* (1.971) [0.088, 0.442]		0.014 (0.213) [-0.066, 0.192]	
Endogenous variables	**R^2**	**Adjusted R^2**	**R^2**	**Adjusted R^2**
Knowledge ambidexterity	0.141	0.095	0.278	0.223
Discrepancy	**Value**	**HI_{95}**	**Value**	**HI_{99}**
SRMR	0.017	0.082	0.089	0.209
d_{ULS}	0.011	0.239	0.616	3.396
d_G	0.007	0.481	1.421	1.824

5 Discussion and Core Conclusions

5.1 Summary of Findings

Managing organizational knowledge is critical in increasingly competitive environments (He et al., 2015). Prior IS literature considers social media to be a key source of information and data (Leonardi, 2014). However, acquiring and generating social media data is not a sufficient condition for creating business value. Monitoring, analyzing, and identifying relevant information is key in transforming social media data into valuable information, knowledge, and business gains (Ransbotham et al., 2015). Firms face difficulties in efficiently selecting and assimilating social media data and converting them into business benefits (Chan et al., 2016). We propose that firms with social media capability can exploit and explore knowledge. Moreover, we argue that the effective application of social media data in business activities can be achieved if firms explore and exploit knowledge and leverage business analytics talent. This study analyzed the impact of social media capability on knowledge exploration and knowledge exploitation and examined the potential moderator role of business analytics talent. The proposed research model was tested using a unique set of archival data from a sample of US firms. After checking eight additional alternative explanations/research models in robustness testing, we are confident that the empirical analysis strongly supports our proposed research model. [12]

How does social media capability influence knowledge exploration and knowledge exploitation? The empirical analysis results show that social media capability enables firms to explore and exploit knowledge because social media are new organizational channels capable of facilitating knowledge management (e.g., acquiring and transferring new knowledge; recombining, modifying, and integrating new/existing knowledge). Social media capability helps firms acquire knowledge from customers, competitors, and suppliers. In this way,

[12] Some of the alternative theoretical explanations were not supported by the empirical analysis, and none of the eight alternative models of the robustness check yields a better overall fit of the estimated model in the context of our sample (Benitez, Henseler et al., 2020). In this sense, we can conclude that none of these alternative models provide a better theoretical model to explain how social media capability and business analytics talent function in companies and help them to create business value. The results of the estimation of these eight alternative models provide additional robustness and credibility to the findings of our study.

firms can identify valuable information from suppliers, competitors, and customers and apply and leverage this useful information to achieve improvements in firm performance. Even though we find that social media capability enables both the exploration and exploitation of knowledge, the effect is greater for knowledge exploration than for knowledge exploitation, suggesting that social media plays a more important role in exploring new knowledge than in exploiting existing knowledge. Furthermore, our results show that business analytics talent amplifies the impact of social media capability on knowledge exploration by helping firms quickly create meaningful new knowledge from unstructured information. Dong and Yang (2020) find that social media diversity and big data analytics have a positive interaction effect on market performance, which is more salient for small than for large firms. Our findings are consistent with Dong and Yang's (2020) work. We show that business analytics talent is a valuable IT resource that can help firms convert unstructured social data (captured through social media capability) into useful new knowledge to be explored, shared, and stored. In this sense, the empirical analysis supports our proposed research model.

Based on our robustness testing, we obtained additional results regarding how knowledge exploration and knowledge exploitation (driven by social media capability and amplified by business analytics talent) affect firm performance. Both exploration and exploitation have been found to help firms increase their business benefits. Organizational knowledge is a resource that is difficult to imitate and may be a source of competitive advantage (Alavi & Leidner, 2001). As an illustrative example of the role of social media and knowledge management in improving firm performance, Dell created a social media platform (http://ww.ideastorm.com/) to acquire and exploit social data from their customers that enabled their customers to submit ideas, vote for other ideas, and comment on the ideas of other customers. Dell managed customers' data to implement the best ideas (e.g., biodegradable packing material), which led to improved firm performance. This shows how effective exploration and exploitation of knowledge can provide an excellent return on firm investment (Dong & Wu, 2015). Indeed, our results suggest that knowledge exploitation has a greater effect on firm performance than knowledge exploration, which is rational and consistent with prior IS research (Benitez, Llorens et al., 2018). The acquisition and creation of new knowledge are related to sensing new business opportunities (Benitez, Llorens et al., 2018; Cui et al., 2019) and affect firm performance. However, the biggest effect on firm performance is realized once the company assimilates, uses, and exploits the knowledge related to the exploitation of business opportunities. Therefore, it is rational to expect that the effect on firm performance of using, leveraging, and applying knowledge (knowledge exploitation) is greater than the creation, sharing, and storage of knowledge (knowledge exploration).

5.2 Key Contributions to IS Research

This study draws on IS literature on knowledge management and the business value of social media to link social media capability and firms' knowledge exploration and knowledge exploitation. This paper contributes to IS research in three ways. First, although the crucial challenge for organizations is to learn how they can develop the ability to effectively select, use, and leverage external social media in order to scan, learn, and internalize knowledge, it remains rather unclear how companies can develop social media capabilities and create business value based on these capabilities. Prior IS research has largely focused on understanding employees' knowledge sharing behavior in enterprise social media (e.g., Beck et al., 2014; Leonardi), user-generated content, and customer engagement in diffusing information on social media platforms (e.g., Bapna et al., 2019). In contrast to prior IS research on this topic, which has emphasized the employee, customer, and user as units of analysis, we focus on the organizational level. We develop the concept of social media capability, explain it theoretically, provide a set of measures that can be built with archival data, and offer empirical evidence on how firms can explore and exploit knowledge from social media. This is the primary contribution of this manuscript to IS research.

Second, although a firm's business analytics talent may perform a critical role in understanding and acquiring new knowledge from big data on customers in social media, this plausible effect has been undertheorized in IS research. Prior IS research has focused mainly on the impact of big data analytics capability on competitive performance (Mikalef et al., 2020) and on its reinforcing role to create synergies and improve market performance (Dong & Yang, 2020). We believe that the extant literature overemphasizes the importance of analytics software and minimizes the significance of people and analytics talent (Conboy et al., 2020). Drawing on Ransbotham et al.'s (2015) managerial paper, we develop the concept and measure of business analytics talent and show how this resource reinforces the relationship between social media capability and knowledge exploration. This study suggests that business analytics talent is a complementary resource of social media capability since they mutually reinforce each other in that the presence of business analytics talent amplifies the impact of social media capability on knowledge exploration. Thus, business analytics talent enables firms to better explore new knowledge derived from external social media. We also propose and build a measure of business analytics talent supported by empirical analysis, which can be used in future impactful IS research. This represents our second major contribution to IS research.

Finally, our study confirmed the proposed research model with consistent estimates, using the PLS estimator and the ADANCO software statistical package. Both IS research and PLS path modeling require the usage of the most up-to-date statistical standards. Using ADANCO, this paper illustrates how to run a confirmatory composite analysis to confirm that the structure of measures is correct. Beyond this, it demonstrated how to evaluate whether the proposed research model is correct by evaluating the overall fit of the estimated model. We integrate this into the eight alternative models that are included in our robustness testing. Our third contribution to IS research is our introduction of the ADANCO software package, our recommendation of its use for future confirmatory IS research, and our illustration of its use in a study on the business value of social media capability.

5.3 Limitations and Avenues for Future IS Research

This paper also has some limitations, which also suggest excellent avenues for further IS research. First, these results can only be generalized to small firms in the US market. Future IS research could investigate whether the proposed research model is also supported in different geographic markets and larger companies. Second, we restricted our focus to a limited number of external social media platforms. This approach implies that the effects explored by this study on knowledge exploration and exploitation can only be associated with firms' external social media. Although we examined three of the most popular external social media platforms (Braojos et al., 2019; Culnan et al., 2010), our research does not explore enterprise/internal social media platforms (e.g., Microsoft Yammer, Facebook Workplace) and other important external social media platforms (e.g., Instagram, LinkedIn). Moreover, cultural differences may influence how firms leverage social media capability and business analytics talent. We encourage IS scholars to investigate these potential differences in future IS studies. For instance, exploring how the external social media platforms used by Chinese firms (e.g., WeChat) and the digital ecosystem of Chinese firms/customers are different from those used by US firms/customers could be an interesting topic for future impactful IS research. Further, IS research could extend this study by examining enterprise social media platforms and other new external social media platforms and including them in conceptualizing social media capability. Third, we are confident that the ingredients used to assess Facebook capability, Twitter capability, and blog capability represent a good proxy to evaluate these constructs, which has also been supported by the confirmatory composite analysis. However, we recognize that our measurements of these constructs may present some "noise" between the conceptualization and the measurements, which is typical when a study uses secondary data. Future IS research could develop perceptual measures for social media capability and validate them through a confirmatory composite/factor analysis, which would offer a valuable means of replicating our study results.

Fourth, the development of social media capability and its exploitation to create business value may be contingent on the firm's social media governance mechanisms. How could the firm's governance structure best maximize the value creation from social media? Future IS research could theorize and empirically examine the effects of social media governance mechanisms on social media's business value. This seems an excellent research topic to explore in future IS research. Fifth, we found a greater effect of social media capability on knowledge exploration than on knowledge exploitation, which offers an opportunity for future research to theorize on moderators of the relationship between social media capability and knowledge exploitation that firms may need, and organizational capabilities that could mediate this relationship. We encourage IS scholars interested in this research topic to theorize and investigate organizational capabilities that can exploit existing knowledge. Finally, this study conceptualizes and finds discriminant validity between social media capability and business analytics talent. However, some IS scholars may consider these concepts to be closely related or even part of each other if they focus on a more general concept such as IT-enabled information management capability. We thus call for further knowledge discovery to address this debate, which represents another exciting avenue for IS research.

Nevertheless, this paper has the capacity to change some of the existing paradigms in IS research in two directions. The first potential change is methodological. The current scenario of IS research provides us with the opportunity to build innovative datasets and search for confirmatory IS research. We hope this study inspires other IS scholars to use our secondary data-based measurements and test their consistency and adequacy through an overall fit evaluation of the saturated model. This study also shows that IS research can confirm the proposed research model through the estimated model's overall fit evaluation. We introduce the ADANCO software package, explain when it could be used, and illustrate how to use it for confirmatory IS research in the research stream of the business value of IT.

The second potential change is related to digital capabilities. The design and execution of digital transformation strategies have become "a must" for companies. This strategic imperative has been accelerated by the COVID-19 pandemic. In the future, exploring new digital resources will require new digital capabilities for firms. These new digital capabilities (e.g., leveraging artificial intelligence, 5G, blockchain) have the capacity to serve business activities and maximize business benefits. However, many of these new digital capabilities will need to be conceptualized and tested empirically in isolation from prior IT capabilities, as was done in this study with social media capability and business analytics talent. We hope this paper inspires others in this direction. In the words of Coco Channel, “I do not do fashion. I am fashion”; similarly, IS research does not do fashionable research, IS research is fashion. Future paradigms in IS research may involve “unframed thinking.” Who wishes to take up this challenge?

5.4 Key Lessons Learned for IT and Business Executives

The findings of this study also provide important lessons learned for IT and business executives. First, developing social media capability enables firms to explore and exploit knowledge. Executives should be aware of the potential benefits associated with the usage of external social media to acquire customer, competitor, and supplier data. Companies can also use social media to promote their products and initiatives to collect valuable opinions, preferences, suggestions for improvement, ideas from customers and suppliers, and competitor’s strategic information. Social media can also be leveraged to co-create knowledge with customers and suppliers. Thus, this study suggests that managers should invest, deploy, and leverage social media to acquire and exploit knowledge. For example, Grupo Expansion (a leading Mexican communication industry holding) has the capacity to use external social media (e.g., Facebook, Twitter) to reach potential customers, run marketing campaigns, and acquire knowledge from current customers and competitors, thus enabling the exploration of new knowledge (Hootsuite, 2020b).

Second, firms can amplify the impact of social media capability on knowledge exploration if they recruit, develop, and retain business analytics talent. This study shows evidence of strategies that can be deployed to win the war for top tech talent. Executives should be aware of the importance of employing specialized business analytics experts, keeping in mind the expected shortage of this market talent. Since business analytics talent is scarce, companies should go the extra mile to attract, retain, and develop such talent (e.g., by developing an outstanding employer branding) and be willing to train those with high potential. Firms with high levels of business analytics talent are in a position to benefit more from social media since social media capability and business analytics talent reinforce each other to attain better knowledge exploration. The new knowledge created and captured today will constitute the base of the firm’s future exploitation activities, which will help to ensure the future survival of the firm. Grupo Expansion also uses business analytics talent to convert external social media data into useful new knowledge. They use Hootsuite Analytics to assess social media metrics (e.g., number of followers and clicks, customer engagement) to better create content and acquire customer knowledge. Andrea Sanchez, the senior specialist of digital products of Grupo Expansion, made the following statement, which is consistent with our findings: “Analytics helps our team to convert data into useful information and specific recommendations. Our digital team can make strategic decisions based on business intelligence, and we are obtaining business benefits” (Hootsuite, 2020b, p. 3).

5.5 Core Conclusions

Social media are disruptive IT resources that can transform firms digitally, build a seamless digital business strategy, and help ensure firms’ long-term survival in the digital disruption era. This paper proposes a research model on social media capability, knowledge exploration, knowledge exploitation, and business analytics talent, finding that social media capability enables firms to explore new knowledge and exploit existing knowledge. We also discovered that business analytics talent reinforces the relationship between social media capability and knowledge exploration. Although social media data have become a gold mine for business intelligence, companies need business analytics talent to reveal useful new knowledge. By drawing on the lens of knowledge exploration and exploitation and business analytics talent, we offer a new theoretical explanation and empirical evidence to the IS research community by investigating social media’s business value through knowledge exploration and exploitation. Of course, IT does matter. Quo Vadis? (Palvia et al., 2020).

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Appendix A

Table A1. Prior IS Research on Social Media and Knowledge Management

Authors	Study title	Journal	Research goal	Key findings
Saldanha et al. (2020)	Turning liabilities of global operations in assets: IT-enabled social integration capacity and exploratory innovation	*Information Systems Research*	Examining whether IT helps firms to overcome the liabilities of global operations in the context of the creation of exploratory innovations	IT-enabled social integration capacity influences exploratory innovation by enabling firms to leverage global cultural diversity and global geographical dispersion
Bapna et al. (2019)	Nurturing online communities: An empirical investigation	*MIS Quarterly*	Understanding the effect of participation of firms in online communities on customer engagement	Firm's posts in online communities interact with customers and are diffused by customers with other users, which diffuse the firm's information and increase customer engagement
Song et al. (2019)	Impact of the usage of social media in the workplace on team and employee performance	*Information & Management*	Analyzing the impact of the usage of social media in the workplace on team and employee performance	Work-oriented social media (DingTalk) and socialization-oriented social media (WeChat) are complementary resources that generate synergies to improve team and employee performance
Yang et al. (2019)	Understanding user-generated content and customer engagement on Facebook business pages	*Information Systems Research*	To examine the antecedents and effects of user content generation in the Facebook business page	The negative customer posts are significantly more prevalent than positive posts. They observed three customer complaints related to product quality, money issues, and social and environmental issues. They found that social complaints receive more likes but fewer comments than quality or money complaints
Davison et al. (2018)	Interpersonal knowledge exchange in China: The impact of *guanxi* and social media	*Information & Management*	To understand the interpersonal knowledge exchange in China	The guanxi lubricates the social media-based communication practices that are central to interpersonal knowledge exchange in China
Fang et al. (2018)	Not all posts are treated equal: An empirical investigation of post replying behavior in an online travel community	*Information & Management*	To investigate the knowledge sharing behavior in an online travel community	Sharing post length and vividness, contributors' expertise and degree centrality, and members' social interactions have significant associations with the number of replying posts in an online travel community
Gunarathne et al. (2018)	When social media delivers customer service: Differential customer treatment in the airline industry	*MIS Quarterly*	To examine when social media affect customer service	Airlines respond to half of the Twitter-based customer complaints compared to the expected full response to the complaints in traditional call centers. These companies respond to complaints on Twitter from customers with more followers

Neely & Leonardi (2018)	Enacting knowledge strategy through social media: Passable trust and the paradox of nonwork interactions	*Strategic Management Journal*	Investigating the effect of the employee's usage of social media on the online and offline knowledge exchange between employees	Employees use social media to exchange work and nonwork content. These interactions affect the curiosity and passable trust between employees but also provoke tensions between them, which affects their knowledge sharing
Van Osch & Steinfield (2018)	Strategic visibility in enterprise social media: Implications for network formation and boundary spanning	*Journal of Management Information Systems*	To explore the effect of enterprise social media-driven visibility on the network formation and boundary spanning	The enterprise social media-driven visibility facilitates organizational members to be involved in diverse network structures, which in turn have implications for distinct boundary-spanning activities
Gunarathne et al. (2017)	Whose and what social media complaints have happier resolutions? Evidence from Twitter	*Journal of Management Information Systems*	To understand whose and what complaints on social media are likely to have happier resolutions	They find those complaining customers who are more influential on Twitter are more likely to be satisfied
Pan et al. (2015)	Integrating social networking support for dyadic knowledge exchange: A study in a virtual community of practice	*Information & Management*	Understanding the role of social media in the effect of virtual communities of practice on knowledge exchange	The integration of social media on a virtual community of practice facilitates the knowledge exchange between friends
Beck et al. (2014)	Knowledge exchange and symbolic action in social media-enabled electronic networks of practice: A multilevel perspective on knowledge seekers and contributors	*MIS Quarterly*	To investigate the impact of enterprise social media on knowledge sharing between employees	Knowledge seekers' characteristics and relational factors drive knowledge exchanges in social media-enabled electronic networks of practice. The communicative act expressed by question-answer pairs impacts the quality of knowledge exchanged between employees in enterprise social media
Kane, Alavi et al. (2014)	What's different about social media networks? A framework and research agenda	*MIS Quarterly*	To establish a framework and research agenda for social media networks	They distinguish between online and offline social media networks and discuss the implications for the social network analysis. They also propose a framework and research agenda for social media networks
Leonardi (2014)	Social media, knowledge sharing, and innovation: Toward a theory of communication visibility	*Information Systems Research*	Examining the effect of enterprise social media on knowledge sharing of employees and the firm's innovation	Enterprise social media increase communication visibility among organizational members and facilitate meta-knowledge (understanding who knows what and whom). Enterprise social media change the way organizational members share knowledge, which can facilitate the development of new products

Mount & Garcia (2014)	Rejuvenating a brand through social media	*MIT Sloan Management Review*	Understanding the impact of social media firm's usage on the brand rejuvenating	Nestle UK used Facebook and YouTube to rejuvenate its Kit Kat brand. They scanned customers' insights and opinions and engaged customers (increased interest in the brand). After that, Nestle UK learned and internalized the customer big data to increase market penetration by 8%
Chau & Xu (2012)	Business intelligence in blogs: Understanding consumer interactions and communities	*MIS Quarterly*	To study how blogs can be used by users to generate content and by companies as a source of business intelligence	They propose an organizational and managerial framework to effectively collect, extract, and analyze blogs related to the topics of interest, reveal novel patterns in the blogger interactions and communities, and answer important business intelligence questions
Chai et al. (2011)	Factors affecting bloggers' knowledge sharing: An investigation across gender	*Journal of Management Information Systems*	Understanding the factors affecting knowledge sharing of bloggers	Bloggers' trust, the strength of social ties, and reciprocity all positively affect their knowledge-sharing behavior. The impact of each factor on such behavior varies by gender
Faraj et al. (2011)	Knowledge collaboration in online communities	*Organization Science*	Exploring the knowledge collaboration of individuals in online communities	The fluidity of the online communities affects the resources and the dynamic of knowledge collaboration among organizational members

Note: Table A1 represents an illustration, and a summary of relevant prior IS research on social media and knowledge management. To create this table, we followed the following procedure. We ran a search by topics in the Web of Science, including selecting multiple keywords: social media, social networking, Facebook, Twitter, blogs, knowledge management, knowledge exchange, exploration, and exploitation. We filtered the results focusing on the most reputable journals in IS and other academic disciplines. The following academic IS journals were especially considered: *MIS Quarterly*, *Information Systems Research*, *Journal of the Association for Information Systems*, *Journal of Management Information Systems*, *European Journal of Information Systems*, *Information Systems Journal*, *Journal of Information Technology*, *Journal of Strategic Information Systems*, *Information & Management*, and *Decision Support Systems*. Our list of leading journals also included top managerial IS journals (e.g., *MIT Sloan Management Review*) and top journals in strategy and organizational theory (e.g., *Strategic Management Journal*, *Organization Science*). After that, we read the abstract of the papers' potential list to select the papers to read, use, and reference. The final selection of relevant prior research on social media and knowledge management was included in Table A1 or referenced in our study's theoretical arguments.

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