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Organizational technological opportunism and social media: the deployment of social media analytics to sense and respond to technological discontinuities

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Abstract

In the last decade, social media has evolved from being an interesting technology used mainly for corporate communication and public relations into a proper business tool. However, one of the most promising area, namely the employment of social media as a source of information and knowledge to support the understanding of technological discontinuities and changes, is largely unexplored. This study addresses the previous issue investigating the role of social media analytics, in term of activities and processes that make sense of social media data, in supporting technological opportunism, which is defined as the organizational capability to sense and respond to technological changes. The results support the existence of a positive and significant relationship between social media analytics deployment and technological opportunism, furthermore they highlight the role of Marketing and IT integration and employee skills as significant antecedents.

Keywords: social media analytics; technological opportunism; organizational performance; structural equation modeling; serial multiple mediations

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1. Introduction

The centrality of social media (SM) in the business and organizational debate is a matter of fact. To cite the most impressive evidence, at the beginning of 2018 active SM users worldwide reached the huge number of 3.19 billion, almost one-third of the world's population; an increase of 362 million over the same period in 2017 (Kemp, 2018).

Investment in SM activities has rapidly increased, and company functions dedicated to SM management have consistently grown, confirming the organizations' willingness to employ SM to enhance performance (Roberts & Piller, 2016a). Despite this rapid growth in managerial interest in SM as a tool for business, its employment in one of the most promising areas, innovation and technological developments, continues to lag (Bhimani, Mention, & Barlatier, 2018; Roberts, Piller, & Lu, 2016).

When academic research about SM began, its primary focus was on the radical changes that SM had brought to corporate communications, public relations, and organization-customer interactions (Kaplan & Haenlein, 2010; Kietzmann, Hermkens, McCarthy, & Silvestre, 2011).

In the years that followed, organizations began to deploy SM as a tool to support both overall business activities such as marketing and customer relationship management (He & Wang, 2015; Trainor, Andzulis, Rapp, & Agnihotri, 2014) and very specific activities such as understanding customer sentiments (Fan & Yan, 2015) or competitive intelligence (He et al., 2015).

Despite managerial awareness of SM's centrality in connecting, interacting, and collaborating with customers, recent managerial literature has called for more academic research on the relationship between SM, innovation, and R&D (Bhimani et al., 2018; Mount & Martinez, 2014).

The central issue is the presence inside SM channels of huge amounts of customer information that can be employed throughout the phases of the innovation funnel: idea creation, R&D, and commercialization (Mount & Martinez, 2014), because SM has the "potential to harness diverse knowledge and foster innovation among a wider network of users and partners." (Du, Yalcinkaya, & Bstieler, 2016, p. 56).

Therefore, in very recent years, some theoretical and empirical studies have addressed the relationship between SM and innovation, particularly with respect to product innovation (e.g., Carr et al., 2015; Martini, Massa, & Testa, 2013; Roberts & Candi, 2014). What emerges is that there is a positive and significant relationship between SM and innovation outcomes (Roberts & Piller, 2016). Notwithstanding the very recent academic interest in the issue of SM's role in innovation processes and technological developments, the literature is scarce, and remarkable gaps remain. In particular, no research has addressed the role of SM in enhancing organizational sensing and responding capabilities with respect to technological changes and trends.

Following the well-established "demand-pull" perspective of "technological discontinuities" (e.g. Adner, 2002; Hoisl, Stelzer, & Biala, 2015; Mowery & Rosenberg, 1979) we argue that SM can be employed as relevant source of information related to customers' "preference discontinuities" that can "result in the disruption of an industry by new technology" (Tripsas, 2007, p. 79).

In the actual context of a highly dynamic market characterized by rapid changes in both customer needs and technological developments (Teece, 2007), organizational capabilities of sensing and responding to external changes are a central issue. The risk of not sensing technological developments and changes is to lose sustainable competitive advantage accrued over years of market success.

There are several examples of successful firms that have lost their competitive positions because of their inability to sense important technological shifts. Following are just two well-known examples: (1) Kodak's failure to pursue the digital revolution in photography (Lucas & Goh, 2009); and (2) Nokia's inability to understand the market's preference for clamshell phones in 2004 (Bhutto, 2005) and its subsequent defeat in the "smartphone battle" (Vuori & Huy, 2015).

Contemporary organizations need the ability to sense and respond to technological discontinuities and changes (Srinivasan, Lilien, & Rangaswamy, 2002): this organizational capability is known in managerial literature as technological opportunism (TO) (Chen & Lien, 2013; Sarkees, 2011; Srinivasan et al., 2002).

Another gap in the previous literature is linked to the choice to directly measure the level of SM technology employment, without considering that data from SM are complex, informal and episodic (He & Wang, 2015). This study addresses the previous gap specifically measuring the organizational level of SM analytics technology-related deployment conceptualized and operationalized as a set of activities and practices that enable organizations to collect and make sense of SM data related to technological discontinuities.

Even if some previous studies have suggested that TO is an antecedent of new ICT and e-business technologies adoption (Lucia-Palacios, Bordonaba-Juste, Polo-Redondo, & Grünhagen, 2014; Srinivasan et al., 2002), we argue that the organizations, which have already adopted SM analytics technologies and practices, can employ them to better understand other business-related technological discontinuities and trends. We derived this theoretical proposition both from the literature and an exploratory study based on in-depth interviews with top managers in highly dynamic and innovative industries.

Besides SM analytics practices rely both on organizational inter-functional projects, typically involving Marketing and IT (Fan & Yan, 2015), and on employees digital analytics skills, which are becoming fundamental because of the skills gap created by the digital era (Leeflang, Verhoef, Dahlström, & Freundt, 2014). We also investigate the two above-mentioned issues in the research model to account for the antecedents of SM analytics technology-related deployment.

This study aims to make at least three contributions to the current debate. First, it aims to contribute to the SM and TO literature, reframing the role of SM inside the TO theoretical framework. Instead of considering TO as an antecedent of SM adoption, we analyze the role of SM in supporting the sensing and responding capabilities in relation to business-related technological discontinuities and developments following the “demand-based view” of technology evolution (Adner & Levinthal, 2001; Tripsas, 2007). Second, it theoretically supports and empirically verifies the role of SM analytics technology-related deployment as an antecedent of TO. Third, it contributes to the TO literature by verifying the importance of inter-functional integration of Marketing and IT functions to enhance organizational TO.

The rest of the paper is organized as follows. In Section 2 it is introduced the theoretical framework, the explorative study, and the hypotheses development. Section 3 describes the research methodology and data collection. The findings are presented in Section 4, and lastly, Section 5 is devoted to discussion and conclusions.

2. Theoretical framework and hypotheses development

2.1. From technology orientation to technological opportunism

The central role of technological changes in strategy development dates back to Nyström's (1979) study of technology-oriented firms.

Firms that can search within their respective technology areas for product ideas based on new technical principles display a higher level of innovativeness than more market-oriented firms (Nyström, 1979).

Table 1 presents the evolution of the theoretical conceptualization in the management literature of firms' ability to cope with technological changes.

This evolution of the literature can be divided into two main periods, with Srinivasan, Lilien and Rangaswamy's (Srinivasan et al., 2002) study as the border between the two.

On the one hand, in the first period, the central conceptualization can be labeled as "technological orientation" (sometimes referred to as "R&D orientation"). This first concept refers to firms' "orientation and commitment to new product programs" (Cooper, 1984, p. 254) and their "ability and will to acquire a substantial technological background and use it in the development of new product" (Gatignon & Xuereb, 1997, p. 78)

Table 1.

Evolution of TO literature

Authors (years)	Technology-related theoretical construct	Antecedents	Outcomes
Nyström (1979)	**Technically oriented**: search within technology areas for product ideas based on new technical principles.	Not considered (NC).	Technically oriented companies display high levels of innovation.
Cooper (1984)	**R&D orientation**: orientation and commitment to new product programs.	NC	Successful NPD programs in terms of sales and profit generation and the success of the new product.
Gatignon & Xuereb (1997)	**Technological orientation**: ability and will to acquire and use a substantial technological background in new product development.	NC	In highly dynamic markets, technological orientation increases innovative product performance.
Srinivasan, Lilien & Rangaswamy (Srinivasan et al., 2002)	**Technological opportunism**: firm's capabilities in sensing and responding to new technology developments	Technological turbulence, adhocracy and clan culture, focus on the future, and TMT advocacy.	New technology adoption.
Zhou, Yim & Tse (2005)	**Technological orientation**: commitment to R&D, acquisition of new technology, application of the latest technology	NC	TO positively affects tech-based innovation that has a positive impact on performance.
Garrison (Garrison, 2009)	**Technological opportunism**: organizational trait providing firms with the capability to sense and respond to new technologies in anticipation of creating sources of competitive advantage.	Organizational size.	New technology adoption.
Sarkees (2011)	**Technological opportunism**: use of firm resources to actively scan markets for disruptive discoveries that will change how firms do business	NC	Revenue, profit, and market value.
Voola, Casimir, Carlson, & Agnihotri (2012)	**Technological opportunism**: actively sensing appropriate technologies and quickly responding to technological developments.	NC	TO positively moderates the relationship between market orientation and e-business adoption.
Chen & Lien (2013)	**Technological opportunism**: an ability to understand and acquire knowledge about new technology developments and the willingness and ability to respond to identified new technologies.	NC	Firm performance (NPD success rate, profitability, sales growth, market share)
Lucia-Palacios, Bordonaba-Juste, Polo-Redondo, & Grünhagen (2014)	**Technological opportunism**: capability to acquire, absorb, and assimilate internal and external knowledge and market information about new technologies to respond to potential opportunities and/or threats.	NC	IT adoption, IT diffusion, firm performance.
Lucia-Palacios, Bordonaba-Juste, Polo-Redondo, & Grünhagen (2016)	**Technological opportunism**: sensing and responding to the technological context	IT use (e.g. Intranet, e-commerce, CRM…), IT human capital, IT vendor support.	NC

Technological orientation primarily refers to the “capability of the organization to develop new technologies, products, and processes” (Srinivasan et al., 2002), in this sense it follows the Resource-Based View (RBV), considering technologic orientation as a complex bundle of resources and capabilities (Barney, 1991; Wernerfelt, 1984) with the ability to sustain new technology development inside the firm.

On the other hand, Srinivasan, Lilien, and Rangaswamy (Srinivasan et al., 2002) provide the foundational theoretical framework to conceptualize firms’ ability to cope with technological changes, shifting toward the Dynamic Capabilities (DC) perspective (Teece, Pisano, & Shuen, 1997).

Rooted in DCs’ theoretical framework, technological opportunism (TO) is defined as a “sense-and-respond capability of firms with respect to new technologies” (Srinivasan et al., 2002). Those authors explicitly identified the two distinct elements that characterize TO: (1) the technology-sensing capability, or the “organization's ability to acquire knowledge about and understand new technology developments, which may be developed either internally or externally”; and (2) the technology-response capability, or the “organization's willingness and ability to respond to the new technologies it senses in its environment that may affect the organization” (Srinivasan et al., 2002).

In the studies that follow the article of Srinivasan, Lilien, and Rangaswamy (Srinivasan et al., 2002), the definitions of TO tend to converge, with only minor integrations or modifications (see Table 1). On the contrary in the recent literature, we see interesting changes in the hypotheses about the possible organizational outcomes generated by TO.

The primary focus of early contributions is on studying the relationship between TO and new technology adoption (Garrison, 2009; Srinivasan et al., 2002). Whereas in more recent studies, the positive effect of TO on organizational performance is also considered (Chen & Lien, 2013; Sarkees, 2011).

Following the previously mentioned TO literature (Chen & Lien, 2013; Lucia-Palacios, Bordonaba-Juste, Polo-Redondo, & Grünhagen, 2014; Sarkees, 2011) and the theoretical micro-foundation of DCs (Teece, 2007), we propose the following hypothesis:

H1. There is a positive relationship between the degree of technological opportunism and firm performance.

2.2. The role of Social Media in enhancing organizational technological opportunism: what emerges from the exploratory study

In order to investigate the role of SM analytics activities and processes in supporting the organizational capabilities of sensing and responding to technological discontinuities and developments, we developed an exploratory study based on multiple case studies (Yin, 2009).

We conducted thirteen semi-structured interviews in six different organizations operating in highly dynamic environments both in terms of technological changes and developments (see Table 2). The total number of interviews is decided on our perception of theoretical saturation (Eisenhardt, 1989), about the topic of employing SM analytics activities and processes to sense technological discontinuities and respond to them.

The average duration of each interview was around 60 minutes; all interviews were recorded and transcribed. Secondary sources such as internal company documents, news published in specialized publications, information from corporate websites and SM profiles were also collected in order to improve triangulation of evidence (Eisenhardt, 1989).

The data are then analyzed in parallel with a cross-case analysis approach (Yin, 2009), in the data analysis process all the interviews were coded together with secondary data with the support of Atlas.ti, a widely employed computer-assisted qualitative data analysis software (Yin, 2009). We first open coded data and then we group the resulting codes in higher order categories with an axial coding approach (Goulding, 2002).

What emerged from data analysis were three high order categories related to the deployment of SM inside organizations:

1. Social Media as "must-have" technologies.
2. Social Media as support in developing a "holistic" view of the external environment.
3. Social Media as support in spotting technological changes and adapting to them.

The first higher order concept emerges, to give an example, in the statement of the respondent (RES) 1 of organization (ORG) 2: "*Social Networks, likes Facebook are increasingly employed by firms, even if they don't understand often all the implications. But at today we have to cope with them and learn fast or the risk is to stay back…*". Also, the RES 1 of ORG 3 suggests: "*nowadays almost all the organizations are using social media, or at least they are trying."*.

Even if firms are not always able to use SM or to understand their potential, it seems that these technologies are a "must-have" in the actual context: "*also a lot of micro and small firms started to use them maybe relying on friends' or cousins'* [ironically stated] *capabilities and knowledge about social media… maybe they will make damages with their way of utilize social media, but they think they must be on Facebook!*" (RES 1 in ORG 4)

These first pieces of evidence suggest that the adoption of SM technologies is a quite taken-for-granted practice nowadays, then researchers can move forward from analyzing the role of TO in supporting SM adoption, and study if SM can enhance TO with regards to other types of technological demand-pull discontinuities.

Actually, firms are already a step forward from using SM as simple communication tools, and they are starting to employ them to understand the external environment better. As RES 2 in ORG 5 states: "*Now on social media, we can see exactly what our competitors do and how customers react to their initiatives.* […] *and of course, we are aware that they can do the same with us*" but "*there are several benefits because now we have a clearer idea of people needs before taking decisions*."

Indeed, the understanding of customer's needs is essential, but information gained from SM can lead to a more "holistic" understanding of the market, in fact, "*social media permit to go beyond the simple understanding of what people want… you can also understand what they think, how they talk, or even what they feel*" (RES 1 in ORG 5), and finally "*social media help in understanding what's going on around you*" (RES 2 in ORG 5).

Table 2.

Interview details

Company	**Field**	**Revenues** (million euro)	**Position**	**Number of interviews**
Organization 1	Fashion	1,674	1. Digital Marketing Manager 2. Social Media Manager	2
Organization 2	Banking	130	1. Head of Marketing 2. IT Manager	2
Organization 3	Businesses association	(80,000 associated firms)	CEO	1
Organization 4	Manufacturing		Head of Marketing	1
Organization 5	Digital services	0.9	1. Founder 2. Co-founder	2
Organization 6	Sport safety	107	1. CEO 2. Head of Marketing 3. Senior Project Manager 4. R&D Senior Developer 5. Senior Product Manager 6. Product Manager	6

Finally, organizations can get insights about technological trends and shifts from the information derived from SM, as RES 5 in ORG 6 suggests: "*the relevant communities of extreme sports lovers often talk about technology related issues or needs on forums, or social media groups… they are kind of experts about what they are passionate about!*" and "*for us having a view on their conversations is important to better understand possible technological needs or trends that are emerging in the community*" (RES 6 in ORG 5).

Moreover, the information derived from SM can enhance organizational responsiveness: "*those information* [derived from forums and social media groups] *can be employed to enhance the comprehension of what happing outside to develop faster the new line of products and to follow the more recent developments in terms of technologies, materials, design…"* (RES 6 in ORG 5).

2.2. The role of Social Media in enhancing organizational technological opportunism: what emerges from the literature

As noted in the introduction, in the early phase of academic research on SM, the primary focus was the radical changes that SM was bringing to corporate communications, public relations, and organization-customer interactions (Kaplan & Haenlein, 2010; Kietzmann et al., 2011).

The idea that the information available on SM channels can be employed in the innovation process is an extremely novel one (Mount & Martinez, 2014) and, as a consequence, recent studies have investigated the role and the importance of SM in relation to organizational innovation (Bashir, Papamichail, & Malik, 2017; He & Wang, 2015; Roberts et al., 2016).

SM technologies "constitute a widely used and powerful means of inbound open innovation activities, enabling a firm to effectively acquire and leverage external knowledge" (Du et al., 2016, p. 56).

As anticipated in the introduction we rely on demand-pull literature of technological discontinuities in order to explain the role of SM in supporting organizational sensing and responding capabilities related to technological changes.

The technological changes can significantly depend on demand-side factors, as Tripsas (2007) suggests, such as: (1) emerging customers' segments with novel preferences (Christensen & Bower, 1996; Christensen & Rosenbloom, 1995); (2) demand heterogeneity (Adner & Levinthal, 2001); and finally, the (3) changes in customer preferences (Abernathy & Clark, 1985; Clark, 1985).

Given SM permit to (1) collect relevant information about shifts in customer needs, (2) gain access to external knowledge about possible technical solutions, and (3) identify emerging trends (Mount & Martinez, 2014; Roberts & Piller, 2016b), we argue that they can play a relevant role in enhancing the identification of the "weak-signals" that shepherd demand-pull technological discontinuities (Hoisl et al., 2015).

But making sense of the possible weak signals on SM is not an easy task because information on SM are “primarily complex, informal and episodic” (He & Wang, 2015, p. 263), and available data are often “qualitative and highly unstructured” (Chan, Wang, Lacka, & Zhang, 2016). If the appropriate analytics and skills are not employed to make sense of the data (e.g., Chen et al., 2012; Davenport, 2006; Leeflang et al., 2014), then the effect of SM as source of technical information could be counterproductive with respect to innovation outcomes (Roberts et al., 2016).

To shed some light on the above-mentioned issue, this study conceptualizes and operationalizes the theoretical construct of “Social Media analytics technology-related deployment” to verify the existence (or not) of a positive relationship between the analytics processes of technology-related information, available on SM, and organizational TO.

The main idea is that given the complex, informal, and episodic nature of the technology-related information present on SM (He & Wang, 2015), they need to be gathered and filtered to make sense of them and to understand their implications for action, but to do so organizations need to develop the processes and skills that work as micro-foundations of sensing capabilities (Teece, 2007).

The micro-foundations of DCs are all the “skills, processes, procedures, organizational structures, decision rules, and disciplines—which undergird enterprise-level sensing, seizing, and reconfiguring capacities” (Teece, 2007, p. 1319).

Firms need to deploy all necessary micro-level activities, processes, and skills for "scanning and monitoring internal and external technological developments" so that they can develop the organizational processes "to garner new technical information […] and shape new products and processes opportunities" (Teece, 2007, p. 1323).

This study conceptualizes SM analytics technology-related deployment as micro-foundational activities, and processes that permit to a firm to make sense of SM data to obtain information about technological changes, helping it not only in better understanding the external environment, but also in making timely decisions (Chen et al., 2012; Fan & Gordon, 2014; Fan & Yan, 2015).

Moreover, SM analytics can generate insights to inform business strategy and optimize collaboration (Kane, 2017), supporting timely and technological savvy decisions; therefore SM analytics technology-related deployment can also positively contribute the technology-response capability (Srinivasan et al., 2002).

Following the evidence form both the exploratory study and the literature review, this study hypothesizes as follows:

H2. There is a positive relationship between the degree of Social Media analytics technology-related deployment and organizational technological opportunism.

2.3. The role of inter-functional integration in supporting Social Media technology-related analytics deployment and skills

One of the most common causes of project failure involving Marketing and IT functions is linked to the divergent goals and backgrounds of these functions (Cooper, Gwin, & Wakefield, 2008). To solve the previously mentioned issue and obtain firm performance from IT-related projects, there is a need to integrate the IT function with other functional areas and departments of the firm (Cooper et al., 2008; Wade & Hulland, 2004).

Given the inter-functional nature of SM analytics activities, which involves (at a minimum) both Marketing and IT functions, there is the need for strong inter-functional integration both to support the adoption and employment of SM technology (Kim & Pae, 2007) and to ensure sharing of the specific knowledge that characterizes each unit (Tsai, 2002). As previously noted, a firm's sensing capabilities are, in general, positively supported by the scanning and filtering of relevant information about external changes and opportunities (Teece, 2007). Indeed in the micro-foundations framework emerges that "information must be filtered, and must flow to those capable of making sense of it" (Teece, 2007, p. 1323), activities that are typically in charge of IT department that assures the collection, storage, filtering and flowing of relevant data and information inside organizations. Then managers must figure out how to interpret those information to understand "which technology to pursue" and "how technology will evolve" (Teece, 2007, p. 1322).

Ultimately the necessary micro-level activities are the responsibility of both the IT department, for the technological and information systems side, and the Marketing function, which can develop a “conjecture or a hypothesis about the likely evolution of technologies, customer needs, and marketplace responses” (Teece, 2007, p. 1323). Therefore, Marketing and IT integration can also directly enhance an organization’s sensing-and-responding capabilities as they relate to new technology developments. Given these arguments, the following hypotheses are developed:

H3. There is a positive relationship between the degree of Marketing/IT integration and Social Media analytics technology-related deployment.

H4. There is a positive relationship between the degree of Marketing/IT integration and organizational technological opportunism.

Another central issue linked to the inter-functional integration of Marketing and IT is the skills gap related to the digitalization of channels and firm-consumer interactions (Yadav & Pavlou, 2014).

This phenomenon is widening the organizational skills gap in terms of expertise in social networking, deep customer analytics, and digital media (Day, 2011), causing a “talent gap” in all of the activities related to the digitalization of organization-customer interactions (Leeflang et al., 2014). The relevant knowledge to address this challenge is dispersed among organizational, “silos” (Day, 2011) such as Marketing and IT functions, and only inter-functional dialogue and learning can enhance the development of “deep expertise in next-generation marketing capabilities” (Day, 2011, p. 184).

Moreover, as noted above, SM data are complex and unstructured (Chan et al., 2016), to make sense of those data it is necessary to employ digital analytical activities that enable understanding of and response to technological changes. These tools and activities are quite novel and require specific skills and knowledge (Westerman, Tannou, Bonnet, Ferraris, & McAfee, 2012) to support related analytics deployment (Germann, Lilien, & Rangaswamy, 2013).

Following these argumentations, this study hypothesizes as follows:

H5. There is a positive relationship between the degree of Marketing/IT integration and the level of Social Media analytics skills.

H6. There is a positive relationship between the level of Social Media analytics skills and the degree of Social Media analytics technology-related deployment.

Following the previously introduced theoretical framework, all of the developed hypotheses are presented in the research model in Figure 1.

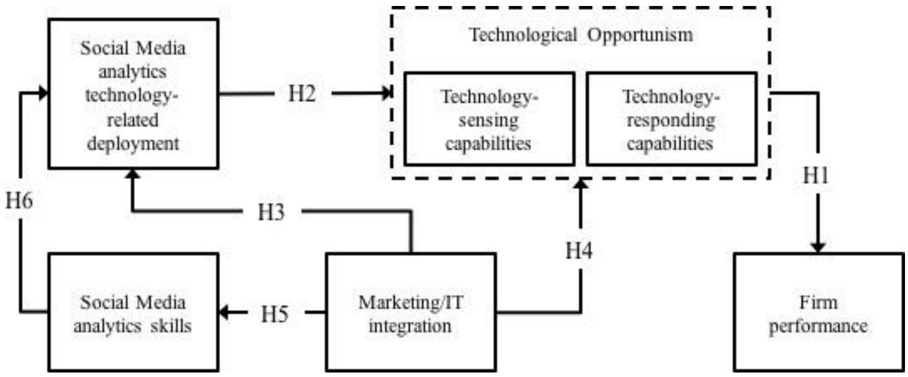

Fig. 1. Research model and hypotheses

3. Research methodology

3.1. Sample and data collection

To test the research model, we developed a survey that employs both constructs already present in the literature and a new scale for measuring SM analytics deployment in a technology sensing-and-responding context (see Table 2). The survey is developed, pre-tested and refined in collaboration with eight experts: four from academia and four from a consultancy and business environment. A first pre-test of the survey was conducted with a sample of 30 firms.

The target respondents' firms were obtained from a state-of-the-art commercial database of all of Italy's limited companies (AIDA – Bureau Van Dijk).

Managers with responsibility for Marketing or related activities are identified as potential respondents because of their engagement in new product and solution information-scanning and -filtering activities. Moreover, they are the most involved in and informed about activities related to sensing and responding activities (Roberts & Grover, 2012). The sample of potential respondents consists of a list of 1200 firms across a broad spectrum of different industries, geographical locations, and dimensions.

To comply with privacy laws, we assured the respondents of anonymity and aggregate use of the data. Next, to increase the response rate and provide participation incentives, the authors offered to provide the respondents with a report of the study's results and invited them to attend a study-related workshop. The responses were collected in approximately twelve weeks.

Two hundred and fifty-one responses were received, which represents a response rate of 20.9%. Of the 251 questionnaires received, 156 were fully completed and 96 were partially completed. In the latter case, missing data treatments were employed to partially recover the information from incomplete surveys.

Organizational key informants represented a wide and equilibrated variety of industries: services (14%); ICT (13.6%); fashion and clothing (12%); manufacturing (8%); and food and beverage (6%). Other industries were also represented with a cumulative percentage of less than 6% (e.g., pharmaceutical, bank and assurance, automotive, chemical, electronics…). In terms of business size, the sample displays the following distribution: 10.2% were micro firms with between 0 and 9 employees; 23.6% were small firms (10-49 employees); 29.6% were medium-sized firms (50-249 employees); 36.6% were large firms (>250 employees).

3.2. Variable definition and measurement

Social Media analytics technology-related deployment: this construct measures the level of deployment of SM analytics inside organizational processes and decision-making related to technological developments and changes. To develop this scale, the study follows an approach similar to the construction of the "technology-use" index (Jayachandran, Sharma, Kaufman, & Raman, 2005; Trainor et al., 2014) and "analytics deployment" multi-items construct (Germann et al., 2013). In addition, these items were developed and refined in collaboration with the previously mentioned eight experts and pre-tested with the sample of 30 respondents. Given the variety of definition of SM analytics tools and processes, we follow the suggestions of two of the academic experts, providing an introductive description of what we intend with "Social Media analytics" and asking the respondent if its view of SM analytics is in line with our conceptualization (see Appendix 1).

Marketing and IT integration: this construct measures the level of integration between the two functions in activities related to inter-functional projects (e.g., CRM, SM analytics), the establishment of project priorities and the generation of new project ideas in close collaboration (Cooper et al., 2008; Peltier, Zahay, & Lehmann, 2013).

Social Media analytics skills: given the importance of digital-related skills in supporting the new scenario of digitalization (Leeflang et al., 2014), especially in analytics activities (Day, 2011) this construct measures personnel's level of SM analytics skills, adapting a previous measurement scale related to customer analytics skills (Germann et al., 2013).

Technological opportunism: to measure the level of organizational TO, this study employs three items to measure technology-sensing capabilities and four items to measure technology-response capability. The first three items are adapted directly from Srinivasan et al. (2002). The items related to responding capability are slightly modified based on advice from our eight experts. Two items are taken directly from Srinivasan et al. (2002), and the other two are derived from the organizational responsiveness framework developed in Homburg et al. (2007).

Firm performance: to test the relationship of TO with firm performance, this study follows previous approaches (Chen & Lien, 2013) to measure both market and financial-related performance, adapting a widely employed measurement scale (Homburg, Grozdanovic, & Klarmann, 2007).

3.3. Preliminary data analysis

Before testing the measurement and structural model, some preliminary data analyses are performed to address the following issues: missing data, non-response bias, multicollinearity, common method variance (CMV).

Given the recent call to address the missing data issue with approaches other than simple pair-wise and list-wise deletion (Newman, 2014), we decided to check the conditions for applying the Full Information Maximum Likelihood (FIML) estimation technique, which is strongly suggested as a treatment for missing data in structural equation modeling (Enders & Bandalos, 2001). Under missing completely at random condition (MCAR), the FIML estimation is unbiased and efficient (Enders & Bandalos, 2001; Newman, 2014).

Table 1. Constructs, items, and sources

Construct	Items #	Scale items (item loading)	Source
Social Media analytics technology-related deployment	SMAD 1	We habitually employ Social Media analytics to collect information about technological changes. (.81)	Developed for this study
	SMAD 2	Information from Social Media analytics are crucial in supporting technology development-related activities. (.85)	
	SMAD 3	We rarely employ information from Social Media analytics to support forecasting of technological changes. (R) (.62)	
	SMAD 4	Decision-making about technological developments is supported by information from Social Media analytics. (.87)	
Marketing and IT integration	MII 1	Marketing is involved with IT in setting new project schedules. (.87)	Peltier et al. (2013)
	MII 2	Marketing is involved with IT in setting new project goals and priorities. (0.90)	
	MII 3	Marketing is involved with IT in generating new project ideas. (.92)	
	MII 4	Marketing and IT frequently discuss the quality of the data system. (.74)	
Social Media analytics skills	SMAS 1	Our people are very good at identifying and employing the appropriate social media analytics tool given the problem at hand. (.86)	Germann et al. (2013)
	SMAS 2	Our people master many social media analytics tools and techniques. (.89)	
	SMAS 3	Our people can be considered as experts in social media analytics. (.90)	
Technological opportunism	TO 1	We are often one of the first in our industry to detect technological developments that might affect our business. (.74)	Srinvasan et al. (2002) and Homburg et al. (2007)
(Technological-sensing TO 1-TO 3)	TO 2	We actively seek intelligence on technological changes in the environment that are likely to affect our business. (.70)	
	TO 3	We periodically review the likely effect of technological changes on our business. (.69)	
(Technological-responding TO 4-TO 7)	TO 4	We respond rapidly if something important happens with regard to technological changes. (.81)	
	TO 5	We quickly implement our planned activities with regard to technological changes. (.79)	
	TO 6	If they do not lead to the desired effects, we are quick to change our activities related to technological changes. (.83)	
	TO 7	This firm lags behind the industry in responding to technological changes. (R) (.84)	
Firm performance		In the last three years, relative to your competitors, how has your business unit performed with respect to:	Homburg et al. (2007)
	FP 1	Achieving the desired profit and revenue level?* (.89)	
	FP 2	Achieving the desired growth?* (.91)	
	FP 3	Achieving/securing the desired market share?* (.87)	
	FP 4	Over the last three years, relative to the industry average, how has your firm performed with respect to return on sales?° (.76)	
		* Seven-point rating scale anchored by “clearly worse” [1], "competition level" [4], and “clearly better” [7] ° Seven-point rating scale anchored by “clearly worse” [1], "industry level" [4], and “clearly better” [7]	

To test for the missing patterns mechanism, we employed Little’s MCAR test. The result supported the presence of the MCAR mechanism given the weak evidence for rejecting the MCAR null-hypothesis of the test (χ^2 (149) = 164.09, p = .19). Next, we applied FIML as the missing data treatment.

To control for non-response bias, we employed late respondents' firms as surrogates for non-respondents (Goode, Lin, Tsai, & Jiang, 2015). The t-test displayed no significant differences, suggesting that non-response bias was not an issue in this study.

Multicollinearity is tested in two steps. First, we verified that all of the EVA scores were above 0.5. Second, the VIF scores are computed. They range from 1.38 to 1.59, safely below the suggested threshold of 5 (Hair, Sarstedt, Ringle, & Mena, 2012).

From the beginning of the data collection, we managed to control the CMV issue following best practices (Woszczynski & Whitman, 2004) such as assuring anonymity to the respondents and avoiding items' social desirability, demand characteristics, and ambiguity (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Once data were collected, we tested for common method bias employing Harman's single-factor test (Podsakoff et al., 2003; Woszczynski & Whitman, 2004); the variance explained by the first single factor in the un-rotated factor matrix was 40.1%, below the 50% threshold. Thus, common method bias was not a serious threat to study validity.

3.4. Measurement model

The measurement model was also tested in terms of reliability, convergent validity, and discriminant validity. Reliability was assessed through analysis of the Cronbach's alpha (CA) and the Composite Reliability (CR) scores, all of which were above the suggested threshold of 0.7 (Hair, Black, Babin, & Anderson, 2010), Moreover, the items' loadings are almost all above 0.7, apart from two factors that are above 0.6, a threshold representing a significant loading given the sample size (Hair et al., 2010).

All of the average variances extracted (AVE) exceed the suggested threshold of 0.5, thus supporting convergent validity (Fornell & Larcker, 1981) (together with the results regarding CR above 0.7 and items loadings above 0.6 (Hair et al., 2010)). Discriminant validity was assessed, verifying that the squared root of AVE is higher than any other the inter-constructs correlation (Fornell &

Larcker, 1981). Each item's outer loading on its assigned construct was greater than all of the possible cross-loadings on other constructs (Farrell, 2010).

Finally, Confirmatory Factor Analysis (CFA) displays adequate fit indexes, suggesting goodness of fit of the measurement model: χ^2 of 365.36 with 199 df and CFI=.95; TLI=.94; RMSEA=.067: SRMR=.059; p=.000.

Table 3.
Assessment of constructs' convergent and discriminant validity.

Constructs	M	SD	CR	CA	AVE	1	2	3	4	5
1. Social Media Analytics deployment	4.26	1.53	.89	.87	.68	**.82**				
2. Marketing and IT integration	4.48	1.65	.93	.93	.76	.54	**.87**			
3. Social Media Analytics skills	4.78	1.43	.96	.96	.88	.44	.42	**.94**		
4. Technological opportunism	4.86	1.21	.93	.93	.65	.54	.49	.46	**.81**	
5. Firm performance	4.81	1.12	.92	.92	.74	.29	.29	.23	.44	**.86**

1. M=mean; SD=standard deviation; CR= Composite reliability; CA= Cronbach's alpha; AVE=average variance extracted.
2. Numbers on the diagonal are the square root of AVEs. The other numbers are correlations among constructs

4. Findings

4.1. Structural model

Given the aim of verifying theoretical hypotheses derived from literature, this study employs covariance-based structural equation modeling (CB-SEM), which is more suitable for theory testing in cases of relatively simple models with sufficiently large numbers of observations (Hair, Hult, Ringle, & Sarstedt, 2014).

The model results (see Fig. 2) show that the model has an adequate fit with the data: χ^2 of 374.79; df=203; CFI=.95; TLI=.94; IFI=.95; RMSEA=.065; SRMR=.072; p=.000.

Following the order of the hypotheses derived from both the exploratory study and the literature review, firstly our model confirms that TO is strongly and significantly associated with firm performance (H1: $\beta = .60$; $p < .001$). Second, H2 is a central hypothesis for this study, given that it suggests a positive association between employing SM in technological and solution information-sensing and -responding capabilities. In the previous literature, the employment of SM, intended only as a technological tool for finding technological and solution information, had shown a negative effect. In contrast, this study focuses on SM analytics, as activities to manage complex and fragmentary SM data to obtain information, which are able to enhance TO: the positive association between SM analytics technology-related deployment and TO has significant support in our structural model (H2: $\beta = .21$; $p < .001$). Another interesting finding of this study involves the importance of changing organizational structure to better integrate the two functions that are more involved in the actual digital transformation context: Marketing and IT.

First, Marketing/IT integration is positively associated both with SM analytics deployment (H3: $\beta = .37$; $p < .001$) and with TO (H4: $\beta = .16$; $p < .01$) because both of these functions are charged with collecting, filtering, and interpreting relevant digital data about external technological changes. Therefore, Marketing/IT integration is also positively associated with the degree of SM analytics skills (H5: $\beta = .47$; $p < .001$) because of their inter-functional nature. Finally, SM analytics skills are positively associated with the degree of SM analytics deployment (H6: $\beta = .51$; $p < .001$) given the specific skills needed to deploy such tools and activities.

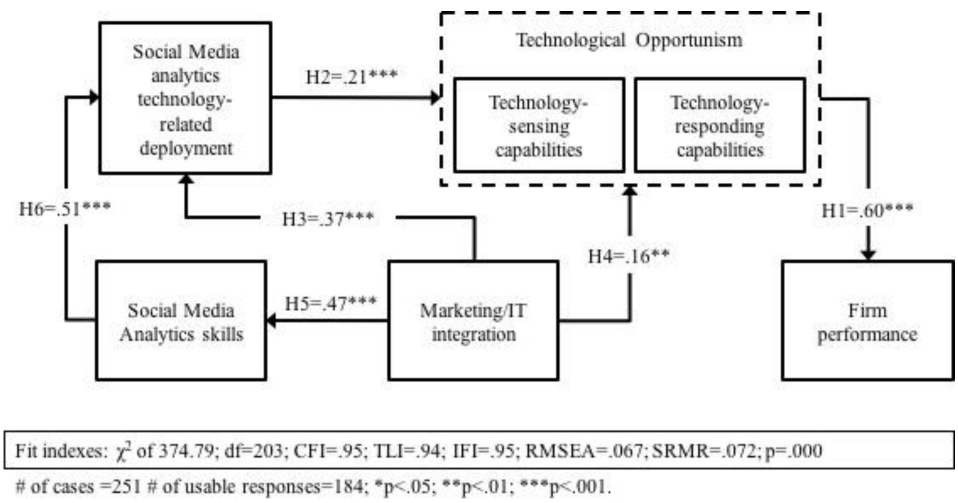

Fig. 2. CB-SEM model

4.2. Serial multiple mediation analysis

To analyze the structure and significance of the mediations that emerge from both the exploratory study and the literature review, we decided to analyze the serial multiple mediation model (Hayes, 2013) that links all of the constructs (except firm performance) to TO and the model that links all of the constructs (including TO) to firm performance (FP).

Employing the SPSS PROCESS script (Hayes, 2013) we analyzed both the above-mentioned serial multiple mediation models. The first model starts from the only exogenous construct of Marketing/IT integration (MII) and arrives at TO via the other constructs of SM analytics skills (SMAS) and SM analytics technology-related deployment (SMAD). Next, we analyzed the model that starts from MII, passing through SMAS, SMAD, and TO, and arriving at FP.

The results (see Table 4) supported the presence of the mediations derived from the literature review and the non-significance of the paths not found in the literature, such as the direct effect of Marketing/IT integration over firm performance when the mediators are present.

Table 4. Indirect effects

Total effect			Direct effect			Indirect effects			
Path	Coef-ficient	t-value	Path	Coef-ficient	t-value	Path	Point estimate	Bias corrected bootstrap 95% confidence interval	
								Lower	Upper
MII->TO	.40***	6.6	MII -> TO	.21**	2.96	Total	.23	.14	.34
						via SMAS	.09	.02	.18
						via SMAS->SMAD	.06	.03	.10
						via SMAD	.08	.03	.17
MII->FP	.19**		MII -> FP	.02°	.22	Total	.17	.09	.27
						via SMAS->SMAD	.04	-.04	.12
						via SMAS->SMAD	.01	-.03	.05
						via SMAS->TO	.03	.01	.08
						via SMAS->SMAD ->TOP	.02	.01	.05
						via SMAD	.01	-.04	.08
						via SMAD->TO	.03	.01	.07
						via TO	.09	.03	.17

1. Bootstrapping of the 95% confidence interval based on 5000 samples

2. * p<.05; **p<.01; ***p<.001; °not significant;

The standardized indirect effects are reported with the bootstrapped confidence intervals calculated with 5000 sample iterations.

In the serial mediation model with TO as the outcome, none of the bootstrapped confidence intervals contain zero, suggesting that all of the indirect effects were significant.

In the second serial mediation model, with FP as the outcome, three indirect effects were not significant; all of them do not consider the presence of TO as the mediator of their relationship with FP and empirically test different paths that directly link SMAD and TO. The other indirect effects, which are significant, all provide paths via TO to reach FP. These results support the findings of the structural model. Therefore, this empirical evidence confirms the absence of other possible paths not found in the literature review and hypothesized in the research model.

Lastly, all the results of the quantitative analysis are triangulated with the other sources of data, collected in the exploratory study, to support the interpretations of the empirical evidence.

5. Discussion and conclusion

5.1. Theoretical implication

From a theoretical point of view, this study makes interesting contributions to the existing literature. First, it contributes to the SM literature introducing first the TO theoretical construct in the debate about the role of SM technologies as the means to collect technological-related information. Second, it contributes by providing strong and significant empirical evidence of the importance of SM in searching for technology-related information; this contrasts with previous research findings of the negative effect of employing SM technology as a source of technical solutions' information. The discrepancy may be attributable to previous studies' exclusive focus on "SM tools" employment without investigating the fundamental role of SM analytics activities to make sense of complex, informal and fragmentary SM data. From a theoretical point of view, this study disentangles the specific role of SM analytics technology-related activities from the more general idea of employing SM as a source of technical information.

The empirical results of this study, suggest that because of the complexity of SM data, the stand-alone employment of SM technologies is inadequate to support the understanding of technological discontinuities and changes. Analytics activities must be deployed to make sense of SM data and support the sensing and responding organizational capabilities related to technological developments.

This study also contributes to the TO literature by verifying the importance of inter-functional collaboration in sustaining TO. Especially in the actual context of digital transformation, the integration of Marketing and IT functions is crucial. Both of these functions involve specific knowledge and competencies that must be integrated to develop technology-related sensing-and-responding capabilities.

5.2. Managerial implication

This study also highlights some interesting managerial implications. First, it corroborates the importance of SM as managerial sources of information. Second, it supports the role of SM analytics activities in sensing and responding to technological developments. Therefore, this study notes the importance of SM analytics activities and organizational SM analytics skills as fundamental antecedents of TO. Both of these aspects are strongly connected with the development of inter-functional integration between Marketing and IT functions.

Another interesting insight for managers is the need to prioritize the development of Marketing/IT integration and collaboration due to the complexity, which has already emerged in the previous literature, of developing inter-functional projects related to these two functions (such as CRM or SM analytics projects). Both of these functions are repositories of important knowledge and capabilities (technological, analytical…) that must be integrated to cope with increasing digitalization. The risk of not developing such integration is that the strong differences between the two functions, in terms of their goals and backgrounds, prevent the development of the knowledge and capabilities necessary to sense and respond to technological changes.

The above-mentioned aspects must be prioritized in the managerial agenda to effectively compete in the actual scenario of digital transformation and rapid technological changes.

5.3. Limitation and future research

Despite its contributions to a relevant theoretical and managerial debate about the role of SM, this study is constrained by some limitations.

First, it relies on survey methodology based on the collection of perceptual data by a single key informant for each firm. Even if considerable efforts were undertaken to ensure the validity of the study and to avoid common method variance, the complete absence of potential biases cannot be assured. Given the importance of checking for inter-rater reliability, future research must address the issue of collecting more than one survey for a single firm.

In order to support the present study's generalizability, we triangulate the results with other sources of data collected in the multiple-case study, given the limitations of perceptual data.

Further studies should also address theoretical issues more than methodological limitations, including the external environmental conditions that moderate the effects of SM analytics on TO and the role of other digital sources of technological-related information.

Finally, this study focuses on Marketing and IT functions as being the most involved in these process of sensing and responding to technological changes employing SM. Future research should also consider the role of collaboration and integration with other important functions that are increasingly challenged by digitalization, such as production, operations, and the supply chain.

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Appendix 1

In the survey, the following lines precede the questions about Social Media analytics deployment.
“Before going on with the survey we ask you to read the following definition and think if it is in line with your view of Social Media analytics:
Social Media analytics can be defined as all the activities and processes of monitoring, analyze and interpret the information, relations, and contents created by users on Social Media, in order to use the insights derived from these analyses in business decision-making.”