Technological Forecasting & Social Change 175 (2022) 121416

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Social media analytics, competitive intelligence, and dynamic capabilities in manufacturing SMEs

Abdeslam Hassani [a,*], Elaine Mosconi [b]

[a] École de Gestion, Université de Québec à Trois-Rivières 3351 Bd des Forges, Trois-Rivières, QC G8Z 4M3, Canada
[b] École de Gestion, Université de Sherbrooke 2500, boulevard de l'Université, Sherbrooke J1K 2R1, Canada

ARTICLE INFO

Keywords:
Social media analytics
Competitive intelligence
Dynamic capabilities
SMEs

ABSTRACT

Dynamic capability is an emerging field for firms facing a turbulent environment. Previous studies highlight that firms with little dynamic capabilities to enhance organizational performance face many survival challenges. This study proposes how small and medium enterprises (SMEs) can enhance their dynamic capabilities through learning mechanisms such as social media analytics and competitive intelligence processes that include the planning, collection, analysis, and dissemination of information. Specifically, this study focuses on the effects of social media analytics on four phases of competitive intelligence to improve the dynamic capabilities within manufacturing SMEs. Social media analytics are better used in certain large companies but less acknowledged in SMEs. However, limited empirical studies have used the dynamic capabilities approach and examined the causal links between social media analytics and competitive intelligence processes. A survey was conducted among 140 manufacturing SMEs in Quebec to obtain a better understanding of this relationship. Accordingly, a closed-structured questionnaire was distributed to the SMEs' chief executive officers and managers. The data collected were analyzed using structural equation modeling. Our research findings show that social media analytics positively affect four phases of competitive intelligence, especially the phases of collection and analysis.

1. Introduction

Small and medium enterprises (SMEs) constitute a majority of the businesses worldwide. They are essential contributors to job creation and global economic development and play a significant role in the development of most economies (Yap and Rashid, 2011). While SMEs have more room for innovation in their organizational practices and often in the use of technological products and processes than large firms, those in the manufacturing sector struggle to increase their competitiveness (OECD, 2019). These SMEs face specific challenges in an unstable environment (Garbellano et al., 2019), with accelerated information changes regarding clients, competitors, suppliers, and technologies, which creates uncertainty and hampers innovation (Bertrand, 2012; Sharma, 1999). To face these challenges, companies need dynamic capabilities (Eisenhardt and Martin, 2000; Teece, 2007). The study of dynamic capabilities, which refers to an organization's capacity to reconfigure operating routines and skillsets and adapt them to environmental turbulence, has become increasingly important in strategic management and organizational theory (Di Stefano et al., 2010; Eisenhardt and Martin, 2000; Teece, 2007; Teece et al., 1997; Zollo and Winter, 2002). In a turbulent environment, organizations need to continuously sense opportunities, seize their value, and periodically reconfigure resources to proactively reposition to encounter threats and explore opportunities (Teece, 2018). To achieve this, Zollo and Winter (2002) suggest that implementing exploration and exploitation routines can lead companies to identify opportunities, modify existing routines, and generate knowledge, leading to a better understanding of their customers' needs and their competitors' activities. Competitive intelligence, a process that includes planning, collection, analysis, and the dissemination of information, can be a systematic way for SMEs to generate knowledge (Luu, 2014) and contribute to developing dynamic capabilities (Garcia, 2017). Competitive intelligence follows a process (Kahaner, 1997) aiming to help organizations collect information from customers, suppliers, competitors, and the business environment to transform them into knowledge (Calof and Wright, 2008; Kahaner, 1997; Oubrich, 2011) for supporting decision-making and enhancing innovation within organizations (Calof and Sewdass, 2020; Hassani and Mosconi, 2021).

Competitive intelligence requires identifying information sources and the use of analytical tools (Bose, 2008). Previous literature shows

* Corresponding author.
E-mail addresses: abdeslam.hassani@uqtr.ca (A. Hassani), elaine.mosconi@usherbrooke.ca (E. Mosconi).

https://doi.org/10.1016/j.techfore.2021.121416
Received 5 March 2021; Received in revised form 29 November 2021; Accepted 1 December 2021
Available online 7 December 2021

that social media analytics can be considered an essential source of data for competitive intelligence (Larson and Chang, 2016). It helps organizations to stay ahead of their competitors (Gupta et al., 2018), enhances the quality of information collected (Chen et al., 2002), and contributes to analytical capability (Garant, 2017). The literature shows that many large organizations, such as General Electric (GE), Intel, TSMC, and Dell, exploit the potential advantages of social media for manufacturers to generate more ideas and develop new products, among other things (Harrysson et al., 2012; Kaplan and Haenlein, 2010). The SMEs should also benefit from social media analytics, which can be construed as a cheaper way to access vital information to enhance competitiveness, compared to other technologies (e.g., access to databases) (Gebremikael et al., 2020; Itani et al., 2017; Leonardi and Vaast, 2016). Despite these advantages, many companies are not familiar with social media analytics to enhance their competitive intelligence processes (Garant, 2017).

Similarly, Zhan et al. (2021) report that the application of social media, especially in the manufacturing industry, is at a primitive stage, which has been explained by most case studies (Bhattacharyya and Dash, 2020; Fischbach et al., 2009; Garant, 2017; He et al., 2015; Montaquila and Godwin, 2016) that have explored the contribution of social media analytics in creating intelligence. Thus, competitive intelligence research based on social media analytics is still limited and immature (He et al., 2015). Specifically, limited research has been conducted on the causal relationship between social media analytics and competitive intelligence using a dynamic capabilities approach, especially in the context of SMEs. Finally, previous studies have discussed the dynamic capabilities related to either social media analytics or process competitive intelligence but have not focused on their combined dynamic capabilities.

From the perspective of dynamic capabilities, this study seeks to help SMEs face challenges in a dynamic environment. It leverages the existing literature, which states that organizations' capabilities, such as social media analytics and process-oriented competitive intelligence, can become the foundation for new dynamic capabilities. Specifically, this study aims to understand the influence of social media analytics on competitive intelligence to improve dynamic capabilities in SMEs. Accordingly, we answer the following research question: do social media analytics positively affect competitive intelligence and each of its phases?

The remainder of this paper is organized as follows. Sections 2 and 3 are concerned with reviewing the literature, research framework, and hypothesis development. In Section 4, we present and describe the research methods. Section 5 presents and discusses the results of empirical data analysis. Section 6 presents the discussion and implications of our research, and Section 7 presents the main conclusions, limitations, and outlines the avenues for future research.

2. Literature review and hypotheses

2.1. Dynamic capabilities

This study is based on the dynamic capabilities view, which according to a fair amount of research, can explain how organizations develop and maintain competitive advantage. Teece et al. (1997) introduce the concept of dynamic capabilities, which refers to an organization's capabilities to reconfigure its resources to meet the dynamic market needs continually. Specifically, Teece et al., 516) define dynamic capabilities as "the organization's ability to integrate, build and reconfigure internal and external competence to address rapidly changing environments." The dynamic capabilities approach is related to the organization's resource-based view for creating a competitive advantage (Chirumalla, 2021).

Previous research (Teece, 2007; Zahra and George, 2002; Zollo and Winter, 2002) proposes the integration of knowledge flows and learning as a dimension of dynamic capabilities. Similarly, Bhatt and Grover (2005) conceptualize dynamic capabilities as an intensification of organizational learning, which helps companies create a competitive advantage. Leonard-Barton (1992, p. 113) defines dynamic capabilities "core capability as the knowledge set that distinguishes and provides a competitive advantage." Leonard-Barton (1992) points out that the core capability includes employee skills, technological systems, and managerial systems, such as organizational structures and processes. Thus, competitive intelligence is a process that helps generate relevant information and knowledge (Wang and Borges, 2013), and may be considered a dynamic capability (Beaugency et al., 2015; Garcia, 2017).

2.2. Competitive intelligence

According to López-Robles et al. (2020), competitive intelligence is the third most frequent research area as found in a recent bibliometric review. Competitive intelligence can be defined as a product (Kahaner, 1997) or a process that includes collection, analysis, interpretation, and dissemination and provides strategic information for use in the decision-making process (Acharya et al., 2018). The Society of Competitive Intelligence Professionals (SCIP and Society of C.I.P., 2015) defines competitive intelligence as a systematic and ethical process of gathering, analyzing, and managing external business information that impacts and affects company plans, decision-making approaches, and operations. Most of the literature defines competitive intelligence as a process that includes several phases, varying between 3 and 13 phases (Bouthillier and Shearer, 2003). Table 1 presents the significant studies describing the phases of the competitive intelligence process.

Although there are many definitions of competitive intelligence as a process that is made up of several phases, there is a consensus among academics and practitioners on four phases: planning, collection, analysis, and dissemination. In the present study, we define competitive intelligence as a process (Fig. 1) comprising planning, collection, analysis, and dissemination of information to monitor the dynamics of the external environment and create a competitive advantage (Bose, 2008; Calof and Wright, 2008; Prescott, 1995).

2.2.1. Planning

The planning phase is essential in the competitive intelligence cycle (Gilad, 1989). The main aim of the planning phase is to establish a collection and analysis plan according to the information types that will be collected, timing, and other constraints (Bose, 2008; Rothberg and Erickson, 2005). In this phase, managers must identify the need for information to optimize the competitive intelligence process (Dishman and Calof, 2008).

Table 1
- Competitive intelligence cycles.

Authors	Competitive intelligence cycle
Porter (1980)	Collection, analysis, communication
Sammon et al. (1984)	Orientation, collection, processing, dissemination, utilization
Gilad (1989)	Collection, evaluation, storage, analysis, dissemination
Calof and Skinner (1998)	Planning and direction, collection, analysis, dissemination
Kahaner (1997)	Planning and direction, collection, analysis, dissemination
Bouthillier and Shearer (2003).	Collection, storage, analysis, dissemination
Bose (2008)	Planning and direction, collection, analysis, dissemination, feedback
Saayman et al. (2008)	Planning, collection, analysis, communication, sensibilization
SCIP (2015)	Planning and direction, collection, analysis, dissemination
du Toit (2015)	Planning, collection, analysis, dissemination

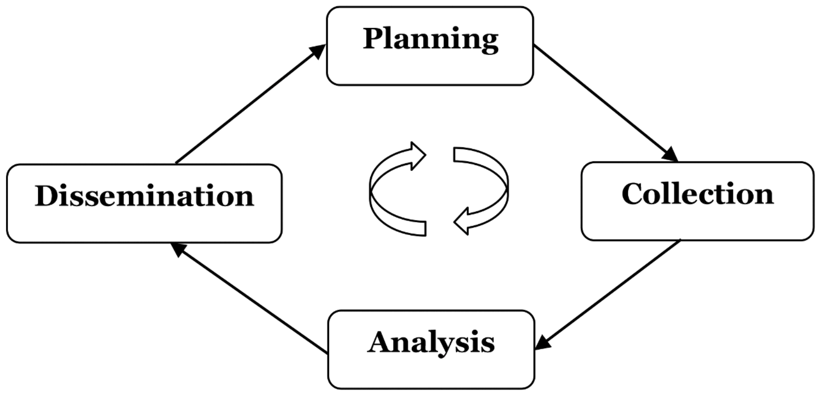

Fig. 1. Competitive intelligence cycle. Adapted from Bose (2008).

2.2.2. Collection

Gathering information is usually a phase that precedes interpretation and action (Thomas and Trevino, 1993). Harrysson et al. (2012) points out that this phase can take 80% of an analyst's time before analyzing information. Before gathering information, it is necessary to identify the different tools and potential sources (Bose, 2008; Bouthillier and Shearer, 2003; Zanasi, 1998). According to Thomas and Trevino (1993), gathering information must follow a rigorous formal process, including identification, selection, and evaluation, which is necessary because some competitors purposely release disinformation, that is, information aimed at misleading the competition (Malhotra, 2005).

2.2.3. Analysis

Called the brain of competitive intelligence (Bouthillier and Shearer, 2003), this is the phase where information is converted into intelligence. It is generally considered the most lengthy and challenging part of the intelligence cycle (Tsitoura and Stephens, 2012). According to Ngamkroeckjoti and Speece (2008), the success of the competitive intelligence process depends significantly on the analysis phase. In this phase, the information collected is analyzed and transformed into intelligence, which can help companies in decision-making (Calof and Skinner, 1998; Dishman and Calof, 2008). To make a correct decision, analysts should use rigorous analysis to provide quality information (Ali et al., 2017).

2.2.4. Dissemination

Producing successful intelligence is not solely dependent on providing the proper findings and disseminating them to senior management. Dissemination aims to communicate the findings of the analysis to managers who have the authority and responsibility to exploit them and make decisions (Dishman and Calof, 2008). The dissemination of intelligent information aims to provide decision-making support for management (Dishman and Calof, 2008) and obtain feedback for future planning or strategic reassessment of CI (Juhari, 2009).

A successful organization should process all available information, understand what has happened, and predict what will happen in the immediate future (Garant, 2017). To do so, companies need organizational processes, such as competitive intelligence, which allows them to collect data, generate information, transform it into knowledge, and develop actions to create a competitive advantage (Agarwal, 2006; Jin and Bouthillier, 2007; Sharp, 2009). Competitive intelligence generates relevant information and knowledge and enhances learning (Wang and Borges, 2013), thus, improving dynamic capabilities (Zollo and Winter, 2002). Beaugency et al. (2015) points out that competitive intelligence helps managers meet the needs of their operational decision-making; hence, it is considered an intermediate dynamic capability. In a similar vein, Riera and Iijima (2019) consider organizational intelligence capabilities, which help organizations assimilate, manage, and use information as dynamic capabilities.

Competitive intelligence is an important external source of information for decision-making (Ross et al., 2012). Vedder et al. (1999) argue that competitive intelligence collects, analyzes, and shares information on external actors, especially competitors. Competitive intelligence also allows managers to gather information and compare their performance with their peer organizations. Lau et al. (2005) report that competitive intelligence can help organizations identify competitors' strengths and weaknesses, enhance business effectiveness, and improve customer satisfaction. Similarly, the case study of Hassani and Mosconi (2021) highlights that competitive intelligence and absorptive capacity enhance SMEs' innovation performance through information collected from clients, competitors, suppliers, and technology.

Organizations using competitive intelligence can create many advantages, such as creating new growth opportunities, minimizing uncertainty, reducing prices, enabling faster responses to changes in the environment, increasing the quality of strategic planning processes, and providing early warnings or alerts for competitive threats (He et al., 2015; Ross et al., 2012). Similarly, Agnihotri et al. (2012) report that competitive intelligence aids in gathering information about common customers, share-of-wallet, competitor pricing, and deployment of social media by competitors. To develop a formal competitive strategy, organizations can use social media to monitor competitors' interactions with customers, identify competitive products, and track competitor activities (Agnihotri et al., 2012). For example, some organizations have produced an accurate view of the product development strategy, with significant implications for research and development (R&D) and marketing strategies because their software developers publicly share information about their work projects (Harrysson et al., 2012). Using social media, organizations can learn more about competitors and customer reactions to their own and competitors' products (Agnihotri et al., 2012).

Social media is an essential source of competitive intelligence (Larson and Chang, 2016). Asri and Mohsin (2020) point out that business executives make inquiries based on customer reviews on social media to enhance decision-making. Previous studies have linked social media analytics and competitive intelligence (Itani et al., 2017; Zhan et al., 2021).

2.3. Social media analytics and competitive intelligence

Social media refers to "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, which allow the creation and exchange of user-generated content" (Kaplan and Haenlein, 2010, p. 61). According to the Global Digital Report 2019, out of the world's total population of 7.676 billion, there are 3.484 billion social media users (Meel and Vishwakarma, 2020).

Social media has become an open stage for discussion, ideology expression, knowledge dissemination, emotions, and sentiment sharing (Meel and Vishwakarma, 2020). Millions of individuals use social media platforms such as Facebook, Twitter, Snapchat, and Instagram to gather information, share experiences (Groothuis et al., 2020), and enhance the interaction between different business partners (Soni et al., 2021). Twitter and Facebook have become the most widely used platforms in applying social media data (Groothuis et al., 2020; Singh et al., 2018; Soni et al., 2021). The study by Ngussa et al. (2020) shows that 50.6% of the respondents use Google classrooms, 30.8% use WhatsApp Group, and 18.6% prefer Zoom to learn about specific topics; social media represents one of the most transformative impacts of information technologies on business (Itani et al., 2017; Zhan et al., 2021), and contributes to the creation of a new world of opportunities and challenges for organizations (Meel and Vishwakarma, 2020). With uncertainty and implausible content everywhere, organizations need to gather credible and accurate information in the era of big data. It is crucial to mitigate the devastating effects of information pollution and contain false content circulation (Nunes and Correia, 2013). To do so, organizations must adopt a rigorous process of collecting and analyzing information, such as big data analytics (Ranjan and Foropon, 2021). Similarly, Fan et al. (2006) point out that assessing the meaning from the gathered information involves many statistical methods and other analytical techniques (e.g., text and data mining, natural language processing, machine translation, and network analysis) in order to create new knowledge. However, by focusing more on the analytics and overlooking the social aspects of decision-making, analytical tools have failed to offer significant information (Meredith and O'Donnell, 2011). For this reason, many authors have proposed social media analytics (Fan and Gordon, 2014; Meel and Vishwakarma, 2020; Zeng et al., 2017) as a tool for collecting and analyzing information.

Social media analytics can be defined as "using advanced informatics tools and analytics techniques to collect, monitor, and analyze social media data to extract useful patterns and intelligence" (He et al., 2015). Social media analytics includes the analysis of customer comments on specific services or products, or structure-based analysis, which looks at social networks and relationships between partners (Gandomi and Haider, 2015). Social media analytics applies advanced informatics techniques and analytical tools to capture, monitor, and analyze social media data to extract useful information and patterns that can be used as essential support for competitive intelligence (Zeng et al., 2017). Social media analytics aims to "derive actionable information from social media in context-rich application settings, develop corresponding decision-making or decision-aiding frameworks, and provide architectural designs and solution frameworks, for existing and new applications that can benefit from the 'wisdom of crowds' through the Web," (Fan and Gordon, 2014; He et al., 2017) using technology and toolsets. Social media analytics is also understood as a tool to harvest information about competitors, customers, and the market more generally (Zhan et al., 2021). Social media analytics may reinforce organizations by changing manufacturers' operations and production planning (Ramanathan et al., 2017). In addition, social media-based information between manufacturing organizations and different actors in the environment becomes efficient and effective (Agnihotri et al., 2012). The literature shows that many organizations use social media analytics to support innovation performance (Scuotto et al., 2017). For example, General Electric uses social media analytics, which allows them to produce, in a short time, thousands of ideas that had not been discussed or published elsewhere, which can reinforce the ideation phase of the innovation process.

Previous studies suggest that social media analytics helps organizations produce intelligence, which, in turn, contributes to creating competitive advantages and business values (Fan and Gordon, 2014). Social media analytics allows not only to identify the right customer segment but also to help people have the right message at the right time (Soni et al., 2021). Harrysson et al. (2012) proposed a cycle connecting social media and phases of competitive intelligence and showed that social media could enhance each phase to a different extent. This report mentions that social media has little effect on some phases of the intelligence cycle, particularly prioritizing exploration and decision-making during the next six to 12 months (Harrysson et al., 2012). However, it can help organizations support the gathering, analysis, and dissemination phases. Indeed, the use of social media analytics to scan the environment, supports competitive intelligence (Kietzmann et al., 2011) and enhances the quality of the collection phase of competitive intelligence (Chen et al., 2002).

Social media analytics improves organizations' competitive intelligence, especially during the analysis phase (Fan and Gordon, 2014; Scuotto et al., 2017). Indeed, in this phase, analysts select rich data from social media for modeling and employ various advanced data analytic methods to analyze the data retained and provide relevant information (Zeng et al., 2017), which contributes to obtaining strategic knowledge and facilitating decision-making for top management. In the context of sales, Andzulis et al. (2012) interviewed a group of sales managers from various industries, arguing that social media analytics affects the prospecting and analysis of customer needs phases in the sales process. The results of a quantitative study by Itani et al. (2017) show a positive relationship between social media and competitive intelligence.

Accordingly, we formally hypothesize the following:

H1: Social media analytics has a positive effect on competitive intelligence.
H1a: Social media analytics has a positive effect on the planning phase.
H1b: Social media analytics has a positive effect on the collection phase.
H1c: Social media analytics has a positive effect on the analysis phase.
H1d: Social media analytics has a positive effect on the dissemination phase.

2.4. Conceptual model

Building on the concepts of social media analytics and competitive intelligence, supported by the above-described theoretical background, Fig. 2 illustrates the conceptual framework of this research.

3. Methodology

3.1. Sample

This study adopted the questionnaire-based survey method to capture causal relationships between constructs and provide generalizable statements on the research setting (Pinsonneault and Kraemer, 1993). Moreover, surveys can accurately document the norm, identify extreme information, and delineate the associations between variables in a sample (Gable, 1994). Survey research is also recommended for explanatory and predictive theory to ensure greater confidence in the generalizability of the results (Straub et al., 2004). In this study, a cross-sectional survey was conducted to collect data and test the research model.

This study used the database of the Center de Recherche Industrielle du Québec (CRIQ), which includes a list of 3800 manufacturing SMEs with fewer than 499 employees, as defined by the Federal Agency for Innovation, Science and Economic Development, Canada. We chose a sample of 533 SMEs from this sampling frame to provide potential respondents based on crucial informant methodology. Segars and Grover (1999) suggest that respondents can be chosen based on their experience, position, and professional knowledge, providing reliable firm characteristics and reducing bias. The key informants included chief executive officers (CEOs), directors, and senior managers.

Three weeks after the initial mailing, we sent a follow-up reminder to managers who did not return the completed questionnaire. All participants were told that the purpose of this study was to contribute to scholarly research to minimize social desirability bias and consequently, there was no right or wrong response. In total, we sent 533 inquiries and

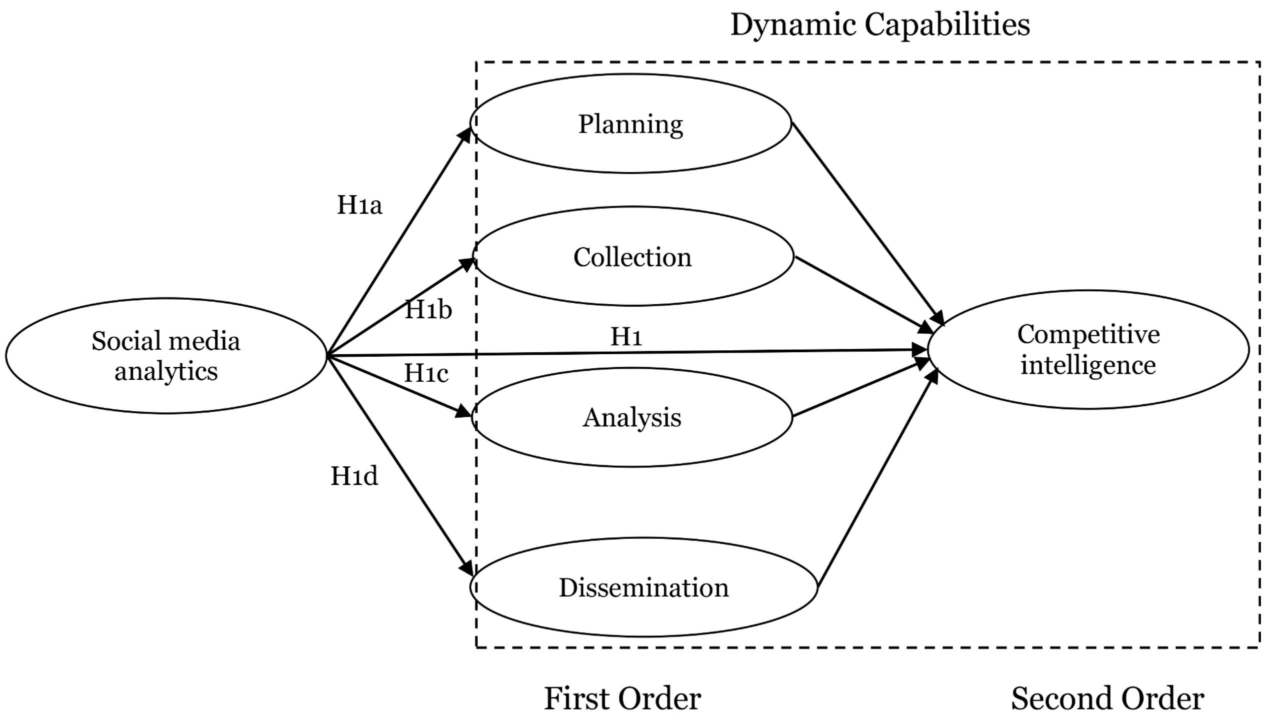

Fig. 2. Social media analytics and competitive intelligence conceptual framework.

received 155 responses, from which we excluded 15 responses that were provided by managers who did not understand the competitive intelligence construct. After this procedure, 140 questionnaires were administered. According to Hoyle (1995), a sample size between 100 and 200 should be sufficient to test the research model using structural equation modeling (Hoyle, 1995). The response rate was 26%. Considering the time slack of SME managers, this response rate can be considered a good online survey for managers (Hausberg and Leeflang, 2019).

3.2. Measures

The constructs were measured using scales developed and validated in extant literature using the positivist approach in this study. We adapted the scales before the primary survey and conducted a pilot study to ensure that the measures were valid and reliable. First, we validated the content in collaboration with practitioners and academics (Hambrick, 1981). We met the directors of many SMEs in different industrial sectors. We presented the questionnaire to the respondents, and collected the data onsite to clarify respondents' questions and ensure that the questionnaires collected were complete and usable. Second, the questionnaire was evaluated by two professors of research methodology and an expert on social media, who suggested some modifications.

After evaluating the questionnaire, we conducted a pilot study to ensure that the measurements were reliable (Churchill, 1979). Measurements were made using 7-point Likert-style scales, where the scale items ranged from 1 (Strongly Disagree) to 7 (strongly agree). We purified all measures to ensure that Cronbach's alpha values were greater than 0.7 (Hair et al., 2016).

Unlike previous research (Abdul-Mohsin et al., 2015; Beal, 2000; Guimaraes et al., 2016; Luu, 2014), we chose to measure the competitive intelligence process with four phases as defined in the literature. Accordingly, we adapted the scales of Juhari (2009) for the planning, collection, and dissemination phases. A 17-item questionnaire adapted from Juhari (2009) and Harrison-Walker's (2001) scale gauged competitive intelligence.

Juhari (2009) has developed these measures to explore the use of the competitive intelligence cycle in SMEs. To measure the planning phase (four items), CEOs and managers were asked how they attached importance to several types of information. The collection phase (four items) was measured by asking them about identifying information sources and selecting information. To measure the dissemination phase (five items), we asked the respondents how they shared the product of the competitive intelligence process within their organizations. Finally, to measure the analysis phase (four items), we utilized the Harrison-Walker's (2001) scale. We asked the respondents how they examined, understood, and extracted the meaning of information with this scale. Social media use (four items) was measured by adapting the Nguyen et al. (2015) scale. This scale focuses on using social media to gather information from sources such as customers, competitors, suppliers, and technology. To examine the validity of the measures, we followed two steps, using 12 and 140 SMEs, respectively.

Table 2
- Demographic profile of respondents.

Dimension	Category	Percentage (%)
Job occupation	Chief executive officer	37.85
	General manager	22.15
	Divisional managers	40
Age	18 – 25 years old	2.14
	26 – 35 years old	10.71
	36 – 44 years old	18.57
	45 – 54 years old	37.85
	55 – 64 years old	25.00
	65 – 75 years old	5.71
Industry	Primary metal industry	27.86
	Furniture and accessories	10.71
	Industrial rubber products	10.00
	Original equipment manufacturing	9.29
	Other good activities	Less than 8.00
	R&D	4.50
	Industrial services	9.07
	Information technology and software	6.43

4. Data analysis and results

4.1. Demographic profile of respondents

Table 2 shows the demographic profiles of the respondents. As we can see, 37.85% of participants were in the age group of 45–54 years, followed by 25.00% of participants age group–55–64 years, and 18. 57% of participants were in the age group of 36–44 years. The results highlight that 37.85% of respondents were chief executive officers, followed by 22.00% of participants who held the position of director-general.

4.2. Measurement model analysis

To assess the hierarchical research model, we used SmartPLS (v. 3.3.3) (Ringle et al., 2015) to estimate the parameters in the outer and inner models. We applied PLS-SEM using the repeated indicators approach with a path weighting scheme and nonparametric bootstrapping (Chin, 2010) with 5000 replications to provide the standard errors of the estimates (Hair et al., 2016). To evaluate the research model, we evaluated the measurement model in terms of construct reliability, unidimensionality, convergent validity, and discriminant validity. Competitive intelligence is a formative second-order hierarchical model with four first-order constructs, with 16 items. Moreover, to evaluate a second-order formative measurement model, as in our case, Henseler et al. (2009) recommend evaluating second-order and first-order constructs. In the first step, we followed Bentler (1990) to confirm a higher-order confirmatory factor analysis (CFA) testing the unidimensionality of the measurement model. The loadings, Cronbach's alpha, convergent validity (AVE), and composite reliability of constructs, were confirmed to do this. Table 3 shows that the unidimensionality of the measurement model is validated by the internal consistency of the items that have loading values greater than 0.7 (Chin, 2010; Hair et al., 2016), the reliability constructs with Cronbach's alpha, which exceeds 0.70 (Hair et al., 2016), and the AVE of each construct, which are greater than 0.50 (Chin, 2010; Hair et al., 2016).

As recommended by Hair et al. (2016), we also ensured discriminant validity to test whether a construct is genuinely distinct from other constructs by empirical standards. To do this, Hair et al. (2016) suggest comparing the square root of the AVE values with the latent variable correlation. The findings (Table 4) show that the square root of the AVE of a construct is higher than its correlations with the other constructs. According to Chin (2010), the latent constructs have different items and are conceptually distinct from each other.

Table 3
- Standardized loadings, reliability, and validity (***$p < 0.001$).

First-order constructs	Indicators	Loadings	Cronbach's Alpha	Composite reliability	AVE
Planning PLN	PLN1	0.87***	0.84	0.89	0.67
	PLN2	0.90***			
	PLN3	0.71***			
	PLN4	0.80***			
Collection COL	COL1	0.90***	0.93	0.95	0.84
	COL2	0.93***			
	COL3	0.92***			
	COL4	0.90***			
	ANL1	0.88***			
Analyze ANL	ANL2	0.92***	0.93	0.95	0.82
	ANL3	0.93***			
	ANL4	0.87***			
Dissemination DIS	DIS1	0.76***	0.84	0.89	0.67
	DIS2	0.86***			
	DIS3	0.82***			
	DIS4	0.83***			
Social media analytics SMA	SMA1	0.86***	0.90	0.93	0.77
	SMA2	0.88***			
	SMA3	0.92***			
	SMA4	0.83***			

Table 4
- Inter-correlations of the first-order latent constructs.

	PLN	COL	ANL	DIS	SMA
PLN	**0.821**				
COL	0.539	**0.914**			
ANL	0.450	0.565	**0.904**		
DIS	0.337	0.412	0.466	**0.818**	
SMA	0.294	0.331	0.420	0.256	**0.874**

In the second step, to assess the validity of the second-order formative construct (competitive intelligence), we tested the weights of first-order constructs, variance inflation factor (VIF) and discriminant validity by assessing the heterotrait-monotrait ratio of correlation measure (HTMT) (Henseler et al., 2015). Table 5 indicates that the weight values are greater than the threshold of 0.1 (Hair et al., 2016).

To check for multicollinearity, we carried out a collinearity diagnostic for the constructs. The analysis shows that the variance inflation factor (VIF) values are less than the threshold of three (Hair et al., 2016, p. 201). In addition, to analyze discriminant validity, heterotrait-monotrait (HTMT) ratio values were evaluated. According to Henseler et al. (2015), the HTMT is the ratio between the average heterotrait-heteromethod correlation and the average monotrait-heteromethod correlation. The results of the HTMT ratios in Table 6 indicate that the values are below the threshold of 0.85, as proposed by Kline (2015).

The results of this study highlight the empirical validation of competitive intelligence as a second-order formative construct comprising planning, collection, analysis, and dissemination phases.

4.3. Common method variance (CMV)

Kock and Lynn (2012) propose testing both vertical and lateral collinearity for all the latent variables in a model. The occurrence of a VIF must be less than 3.3 (Kock and Lynn, 2012). In our case, all the VIF values are less than 3, which indicates that the research model does not present a common method bias (Kock, 2015). We also investigated the common method variance using procedural techniques. We ensured rigor in the questionnaire design by clarifying the ambiguous elements during the validation of the content with the managers of SMEs. We also clarified the study objectives with adequate flexibility in response options, using appropriate attention checkers, and finally, ensuring the anonymity and confidentiality of responses (Esfandiar et al., 2020).

Finally, we estimated the goodness of fit, as proposed by Hair et al. (2016). Given that this study presents a complex model because the endogenous variable is a second-order formative construct, Tenenhaus et al. (2005) propose assessing the global validity of this model type by calculating the GoF. Additionally, this index is applied to both reflective and formative latent variables (Vinzi et al., 2010). To do this, we used the following formula: $GoF = \sqrt{(AVE \times R^2)}$, and the results show that the GoF value is 0.39, which is greater than 0.36 proposed by Hair (2009).

4.4. Structural model analysis

After obtaining acceptable results for the measurement model, we analyzed the research hypotheses by testing the path coefficients. Table 7 presents the empirical results of the structural model, including

Table 5
- Weights of competitive intelligence latent variables (***$p < 0.001$).

Construct	Latent variables	Weight	*t*-value
Competitive intelligence COM-INT	PLN	0.27***	11.761
	COL	0.37***	16.174
	ANL	0.37***	15.925
	DIS	0.28***	9.832

Table 6
- Heterotrait-monotrait (HTMT) ratio.

	PLN	COL	ANL	DIS
PLN				
COL	0.503			
ANL	0.609	0.608		
DIS	0.404	0.457	0.517	
SMA	0.323	0.360	0.459	0.292

Table 7
- Results.

		Path coefficients	t-value	Support
H1: Social media	→ competitiveintelligence	0.42***	5.999	Yes
H1a: Social media	→ planning	0.29***	3.704	Yes
H1b: Social media	→ collection	0.33***	4.053	Yes
H1c: Social media	→ analysis	0.42***	5.588	Yes
H1d: Social media	→ dissemination	0.25***	2.985	Yes

***$p < 0.001$.

the path coefficient values and significance values related to the paths. To assess the structural model, we used the bootstrap re-sampling (5000) process (Hair et al., 2016).

Given that competitive intelligence is a formative, second-order construct, and explained at 100% by planning, collection, analysis, and dissemination, the effect of social media on competitive intelligence was almost null. In this case, Hair et al. (2016) propose connecting the exogenous variable to first-order constructs and then calculating the total effect of the exogenous variable (social media) on the second-order construct (competitive intelligence).

The structural model indicates that social media has a strong positive effect on competitive intelligence (β = 0.42, t= 5.999, p< 0.001), which supports H1. A positive influence was found between social media and planning (β = 0.29, t= 3.704, p< 0.001), supporting H1a. The results also show a positive relationship between social media use and the collection of information (β = 0.33, t= 4.053, p< 0.001), providing support for H1b. The findings from the analysis show that social media has a strong positive effect on the analysis of information (β = 0.42, t= 5.588, p< 0.001), which supports H1c. Finally, a positive relationship between social media and dissemination of information (β =0.25, t= 2.985, p< 0.01), provides support for H1d.

Structural model evaluation requires checking variance R^2 and Stone-Geisser coefficient Q^2, which provides the relevance and predictive power of the research model (Chin and Dibbern, 2010; Hair et al., 2011; Henseler et al., 2009). To check R^2, we utilized Smart P.L.S. with a two-stage approach, as proposed by (Anderson and Gerbing, 1988). The R^2 calculated was 20.60% (t= 3.481, p= 0.001), which was positive and significant. To assess Q^2, we used a blindfolding technique (Hair et al., 2016), and the Q^2 value was 0.42. According to Chin and Dibbern (2010), our research model presents a large prediction because the Q^2 value is greater than the threshold of 0.35.

We also checked the effect size f^2 (Cohen, 1988; Hair et al., 2016) of social media on competitive intelligence. The effect size f^2 calculated was 0.26 (t= 2.340, p= 0.019), which can be considered as a large effect (Cohen, 1988).

5. Discussion

This research investigates the influence of social media analytics on competitive intelligence, including its four phases, to improve dynamic capabilities within SMEs, and encounter challenges in the dynamic environment. Fig. 3 summarizes the estimation of the path coefficients and the subsequent results of hypothesis testing.

The empirical results of our study highlight that the social media analytics has a positive effect on competitive intelligence, including the planning, collection, analysis, and dissemination phases. These results reinforce the postulations of the theoretical study (Harrysson et al., 2012) and empirical studies (He et al., 2013; Itani et al., 2017; Ranjan and Foropon, 2021) that have argued that social media analytics has a positive effect on competitive intelligence, especially in the collection and analysis phases. For example, the study of Groothuis et al. (2020) shows that social media use, specifically Facebook, positively influences intelligence activities, which in turn influences the decision-making process. Additionally, Facebook allows organizations to create relationships with consumers and foster a brand's performance (Fulgoni, 2016).

The positive effects of social media analytics on the four phases of the competitive intelligence process mean that SMEs using social media will understand market trends, identify information needs, and conduct better competitive intelligence planning. The adoption of social media analytics may also help SMEs to identify the potential sources of information and capture the relevant information from the immediate environment, such as customers, competitors, suppliers, and technology, which improve the collection phase. Using data related to social media and adopting analytic techniques, allows SMEs to extract relevant information, especially from unstructured data (Ranjan and Foropon, 2021; Toker et al., 2016), boost analysis of the phase, and create knowledge, which in turn enhances competitive intelligence (Luu, 2014). The dissemination of competitive intelligence product/knowledge could reinforce social intelligence within SMEs, which aids managers in responding to customer needs and preferences (Luu, 2014; Toker et al., 2016) and create business value (Riera and Iijima, 2019).

This study, based on the dynamic capabilities approach, aimed at understanding how social media analytics and competitive intelligence processes can contribute to developing or improving dynamic capabilities within SMEs. The results of this study suggest that to face the challenges of the market's dynamic needs, SMEs must adopt both a competitive intelligence process and organizational capabilities, such as social media analytics. Kogut and Zander (1992) point out that dynamic capabilities result from the recombination of organizational skills, competencies, and routines. Indeed, the association of social media analytics and a competitive intelligence process could emphasize the importance of SMEs in developing a new competitive vision by using the relevant information and knowledge (Luu, 2014; Wieneke and Lehrer, 2016), which in turn may improve their dynamic capabilities (Zollo and Winter, 2002). Similarly, Hassani's (2020) thesis results reveal that the combination of a competitive intelligence process and technological capabilities, especially in business analytics, constitutes a dynamic capability that mediates the relationship between environmental turbulence and innovation performance in manufacturing SMEs. Similarly, Xu and Kim (2014) suggest that competitive intelligence capabilities promote sense and response strategies, enabling dynamic capabilities.

5.1. Theoretical contribution and managerial implications

This study proposes and tests a research model that identifies a positive and significant relationship between social media analytics and competitive intelligence, including its four phases: planning, collection, analysis, and dissemination of information. The results of this research lead to several important findings that have both theoretical and managerial implications. First, it is among the first studies to examine competitive intelligence as a process that includes four phases using a causal relationship approach. Although there is a rich body of literature on the competitive intelligence process with several phases, it was difficult to identify a quantitative study using competitive intelligence as a second-order formative construct. Second, the results of this study provide empirical validity for competitive intelligence as a second-order

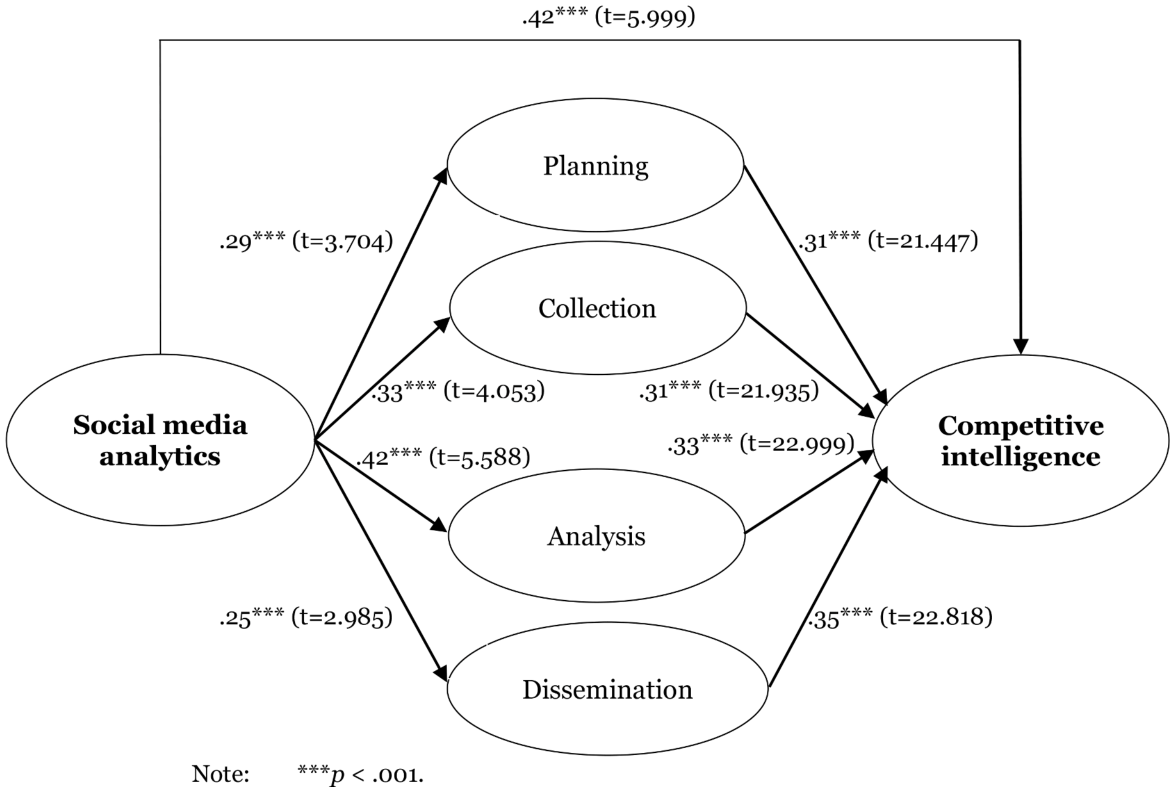

Fig. 3. social media analytics and competitive intelligence structural model path coefficients Note: $^{***}p < 0.001$.

formative construct, which can be used in future research. Third, apart from the theoretical study of Harrysson et al. (2012), this study can be considered a crucial empirical research, examining the effects of social media analytics on the planning, collection, analysis, and dissemination phases of a competitive intelligence process. Finally, to the best of our knowledge, no studies have yet examined how developing or improving dynamic capabilities can be accomplished using a combination of social media analytics and competitive intelligence processes. This study highlights that the adoption of social media analytics and competitive intelligence processes may help create more knowledge, reinforce organizational learning, and, in turn, contribute to dynamic capabilities.

A competitive intelligence process represents an intermediate dynamic capability (Beaugency et al., 2015; Zollo and Winter, 2002), and its enhancement within SMEs is necessary to face external challenges. To do so, managers should adopt process-oriented dynamic capabilities (Kim et al., 2011; Wamba et al., 2017) to enhance their capacity to improve, adapt, and reconfigure their organizational processes, which can contribute to achieving cost reduction, business intelligence, and learning (Bhatt and Grover, 2005). This study helps practitioners understand that in a dynamic environment, facing challenges related to information change about customers, competitors, suppliers, and technology requires a reconfiguration of their resources, thus creating more knowledge to improve their dynamic capabilities. It also provides a helpful direction for SMEs to integrate social media analytics as a tool for developing social intelligence and increasing business value (Toker et al., 2016). Given that social media costs less than other technologies, decision-makers in manufacturing SMEs should invest in social media and analytics technology to have a greater volume of digitized information to draw on, to change their management practices and increase productivity benefits (Brynjolfsson and McElheran, 2016). Considering the lack of commercial skills in SMEs (Huang et al., 2004), social media analytics can also help strengthen commercial capacity by adapting sales behaviors (Itani et al., 2017; Marshall et al., 2012).

6. Conclusions, limitations, and future research

Our empirical study is grounded in theory and tested using reliable data and survey instruments. It highlights how SMEs can improve their dynamic capabilities using learning mechanisms (Zollo and Winter, 2002) such as social media analytics and competitive intelligence processes. Nevertheless, it presents some limitations that can be seen as an opportunity for further research. First, note that we conducted the study within products and services SMEs in the manufacturing sector, which presents a large characteristic heterogeneity. We believe that the replication of the conceptual model in a specific context would enhance its generalizability. Second, competitive intelligence is a process that managers can use to enhance dynamic capabilities to face challenges related to turbulent environments and create competitive advantage. It will be more relevant to integrate firm performance or competitive advantage as a dependent variable into the conceptual model and environmental turbulence as a control variable. Third, we used cross-sectional data in the quantitative analyses in our study. Rindfleisch et al. (2008) criticize this approach for several reasons, including the presence of standard method variance bias. Future research should implement a longitudinal design with matched data collected during different periods. In addition, our study examined the critical role of social media as a tool for collecting, analyzing, and sharing information to improve competitive intelligence within manufacturing firms. However, the extent to which the analysis of the collected information was at the individual or collective level is unknown.

Future research should explore the link between social media and collective intelligence. In this study, we highlighted some types of social media platforms without additional details. Future research should study specific social media platforms, such as Facebook, and explore their advantages for SMEs. Indeed, millions of people use Facebook for various activities, especially for learning (Ngussa et al., 2020). People spend an average of 7 h per month on Facebook, which is more than the time they spend on other social media platforms (Groothuis et al., 2020).

Finally, this study did not consider respondents' basic information and profiles (for example, whether young CEOs and managers use more social media analytics than older CEOs and managers). This information could improve the quality of the data analysis (Singh et al., 2018).

CRediT authorship contribution statement

Abdeslam Hassani: Methodology, Data curation, Supervision. **Elaine Mosconi:** Methodology, Data curation, Supervision.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.techfore.2021.121416.

References

Abdul-Mohsin, A.M., Abdul-Halim, H., Ahmad, N.H., 2015. Competitive intelligence among SMEs: assessing the role of entrepreneurial attitude orientation on innovation performance.
Acharya, A., Singh, S.K., Pereira, V., Singh, P., 2018. Big data, knowledge co-creation and decision making in fashion industry. Int. J. Inf. Manag. 42, 90–101. https://doi.org/10.1016/j.ijinfomgt.2018.06.008.
Agarwal, K.N., 2006. Competitive intelligence in business decisions - an overview. Compet. Forum 4, 309–314.
Agnihotri, R., Kothandaraman, P., Kashyap, R., Singh, R., 2012. Bringing "social" into sales: the impact of salespeople's social media use on service behaviors and value creation. J. Pers. Sell. Sales Manag. 32, 333–348. https://doi.org/10.2753/PSS0885-3134320304.
Ali, S., Miah, S.J., Khan, S., Ali, S., Miah, S.J., Khan, S., 2017. Analysis of interaction between business intelligence and SMEs: learn from each other. JISTEM J. Inf. Syst. Technol. Manag. 14, 151–168. https://doi.org/10.4301/s1807-17752017000200002.
Anderson, J.C., Gerbing, D.W., 1988. Structural equation modeling in practice: a review and recommended two-step approach. Psychol. Bull. 103, 411–423. https://doi.org/10.1037/0033-2909.103.3.411.
Andzulis, J, Panagopoulos, N.G., Rapp, A., 2012. A Review of Social Media and Implications for the Sales Process. J. Pers. Sell. Sales Manag. 32, 305–316. https://doi.org/10.2753/PSS0885-3134320302.
Asri, D.A.A.M., Mohsin, A.M.A., 2020. Competitive intelligence practices and organizational performance linkage: a review. J. Intelek 15, 101–115. https://doi.org/10.24191/ji.v15i2.311.
Beal, R.M., 2000. Competing effectively: environmental scanning, competitive strategy, and organizational performance in small manufacturing firms. J. Small Bus. Manag. 38, 27–47.
Beaugency, A., Sakinç, M.E., Talbot, D., 2015. Outsourcing of strategic resources and capabilities: opposing choices in the commercial aircraft manufacturing. J. Knowl. Manag. 19, 912–931. https://doi.org/10.1108/JKM-01-2015-0040.
Bentler, P.M., 1990. Comparative fit indexes in structural models. Psychol. Bull. 107, 238–246. https://doi.org/10.1037/0033-2909.107.2.238.
Bertrand, J., 2012. Renforcement De La Capacité D'évaluation Des Risques Des Projets De Développement De Nouveaux Produits Dans Les PME. Université du Québec à Trois-Rivières, Trois-Rivières (phd).
Bhatt, G.D., Grover, V., 2005. Types of information technology capabilities and their role in competitive advantage: an empirical study. J. Manag. Inf. Syst. 22, 253–277. https://doi.org/10.1080/07421222.2005.11045844.
Bhattacharyya, J., Dash, M.K., 2020. Investigation of customer churn insights and intelligence from social media: a netnographic research. Online Inf. Rev. 45, 174–206. https://doi.org/10.1108/OIR-02-2020-0048.
Bose, R., 2008. Competitive intelligence process and tools for intelligence analysis. Ind. Manag. Data Syst. 108, 510–528. https://doi.org/10.1108/02635570810868362.
Bouthillier, F., Shearer, K., 2003. Assessing Competitive Intelligence Software: A Guide to Evaluating CI Technology. Information Today, Inc.
Brynjolfsson, E., McElheran, K., 2016. The rapid adoption of data-driven decision-making. Am. Econ. Rev. 106, 133–139. https://doi.org/10.1257/aer.p20161016.
Calof, J., Sewdass, N., 2020. On the relationship between competitive intelligence and innovation. J. Intell. Stud. Bus. 10, 32–43. https://doi.org/10.37380/jisib.v10i2.583.
Calof, J.L., Skinner, W., 1998. La veille concurrentielle : le meilleur des mondes pour les gestionnaires. Optim. La revue de Gest. du Sect. Public 28, 6.
Calof, J.L., Wright, S., 2008. Competitive intelligence: a practitioner, academic and inter-disciplinary perspective. Eur. J. Mark. 42, 717–730. https://doi.org/10.1108/03090560810877114.
Chen, H., Chau, M., Zeng, D., 2002. CI Spider: a tool for competitive intelligence on the Web. Decis. Support Syst. 34, 1–17. https://doi.org/10.1016/S0167-9236(02)00002-7.
Chin, W.W., 2010. How to write up and report PLS analyses. Handbook of Partial Least Squares. Springer, pp. 655–690.
Chin, W.W., Dibbern, J., 2010. An introduction to a permutation based procedure for multi-group PLS analysis: results of tests of differences on simulated data and a cross cultural analysis of the sourcing of information system services between Germany and the USA. In: Esposito Vinzi, V., Chin, W.W., Henseler, J., Wang, H. (Eds.), Handbook of Partial Least Squares: Concepts, Methods and Applications, Springer Handbooks of Computational Statistics. Springer, Berlin, Heidelberg, pp. 171–193. https://doi.org/10.1007/978-3-540-32827-8_8.
Churchill, G.A.J., 1979. A paradigm for developing better measures of marketing constructs. J. Mark. Res. 16, 64–73.
Cohen, J., 1988. Statistical Power Analysis for the Behavioral Sciences, 2nd ed. ed. L. Erlbaum Associates, Hillsdale, N.J.
Di Stefano, G., Peteraf, M., Verona, G., 2010. Dynamic capabilities deconstructed : a bibliographic investigation into the origins, development, and future directions of the research domain. Ind. Corp. Chang. 19, 1187–1204. https://doi.org/10.1093/icc/dtq027.
Dishman, P.L., Calof, J.L., 2008. Competitive intelligence: a multiphasic precedent to marketing strategy. Eur. J. Mark. 42, 766–785. https://doi.org/10.1108/03090560810877141.
du Toit, A.S.A., 2015. Competitive intelligence research: an investigation of trends in the literature. J. Intell. Stud. Bus. 5, 14–21. https://doi.org/10.37380/jisib.v5i2.127.
Eisenhardt, K.M., Martin, J.A., 2000. Dynamic capabilities: what are they? Strateg. Manag. J. 21, 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11<1105::AID−SMJ133>3.0.CO;2-E.
Esfandiar, K., Dowling, R., Pearce, J., Goh, E., 2020. Personal norms and the adoption of pro-environmental binning behaviour in national parks: an integrated structural model approach. J. Sustain. Tour. 28, 10–32. https://doi.org/10.1080/09669582.2019.1663203.
Fan, W., Gordon, M.D., 2014. The power of social media analytics. Commun. ACM 57, 74–81. https://doi.org/10.1145/2602574.
Fan, W., Wallace, L., Rich, S., Zhang, Z., 2006. Tapping the power of text mining. Commun. ACM 49, 76–82. https://doi.org/10.1145/1151030.1151032.
Fischbach, K., Gloor, P.A., Schoder, D., 2009. Analysis of informal communication networks – a case study. Bus. Inf. Syst. Eng. 1, 140–149. https://doi.org/10.1007/s12599-008-0018-z.
Fulgoni, G.M., 2016. In the digital world, not everything that can be measured matters: how to distinguish "valuable" from "nice to know" among measures of consumer engagement. J. Advert. Res. 56, 9–13. https://doi.org/10.2501/JAR-2016-008.
Gable, G.G., 1994. Integrating case study and survey research methods: an example in information systems. Null 3, 112–126. https://doi.org/10.1057/ejis.1994.12.
Gandomi, A., Haider, M., 2015. Beyond the hype: big data concepts, methods, and analytics. Int. J. Inf. Manag. 35, 137–144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007.
Garant, A., 2017. Social media competitive analysis and text mining: a case study in digital marketing in the hospitality industry.
Garbellano, S., Da Veiga, M., do, R., 2019. Dynamic capabilities in Italian leading SMEs adopting industry 4.0. Meas. Bus. Excell. 23, 472–483. https://doi.org/10.1108/MBE-06-2019-0058.
Garcia, A.E.G., 2017. A inteligência competitiva E O desenvolvimento De capacidades dinâmicas Nas organizações. Rev. Ibero-Am. de Estratég. (RIAE) 16, 69–90. https://doi.org/10.5585/riae.v16i1.2439.
Gebremikael, F., Szmerekovsky, J.G., Chris, E., 2020. AHP based framework in driving intelligence from social media to improve organizational performance: an exploratory study. J. Bus. Behav. Sci. 32.
Gilad, B., 1989. The role of organized competitive intelligence in corporate strategy. Columbia J. World Bus. 24, 29–35.
Groothuis, D., Spil, T., Effing, R., 2020. Facebook marketing intelligence. In: Proceedings of the Hawaii International Conference on System Sciences 2020 (HICSS-53).
Guimaraes, T., Thielman, B., Guimaraes, V.C., Cornick, M., 2016. Absorptive capacity as moderator for company innovation success. Int. J. Acad. Bus. World 10, 1–18.
Gupta, S., Kar, A.K., Baabdullah, A., Al-Khowaiter, W.A.A., 2018. Big data with cognitive computing: a review for the future. Int. J. Inf. Manag. 42, 78–89. https://doi.org/10.1016/j.ijinfomgt.2018.06.005.
Hair, J., 2009. Multivariate Data Analysis. Faculty Publications.
Hair, J.F., Hult, G.T.M., Ringle, C., Sarstedt, M., 2016. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). SAGE Publications.
Hair, J.F., Ringle, C.M., Sarstedt, M., 2011. PLS-SEM: indeed a silver bullet. J. Mark. Theory Pract. 19, 139–152.
Hambrick, D.C., 1981. Environment, strategy, and power within top management teams. Adm. Sci. Q. 26, 253–275. https://doi.org/10.2307/2392472.
Harrison-Walker, L.J., 2001. The measurement of a market orientation and its impact on business performance. J. Qual. Manag. 6, 139–172. https://doi.org/10.1016/S1084-8568(01)00035-9.
Harrysson, M., Metayer, E., Sarrazin, H., 2012. How 'social intelligence' Can Guide Decisions. McKinsey.
Hassani, A., Mosconi, E., 2021. Competitive intelligence and absorptive capacity for enhancing innovation performance of SMEs. JISIB 1. https://doi.org/10.37380/jisib.v1i1.692.
Hausberg, J.P., Leeflang, P.S.H., 2019. Absorbing Integration: empirical evidence on the mediating role of absorptive capacity between functional-/cross-functional integration and innovation performance. Int. J. Innov. Manag. 23.
He, W., Shen, J., Tian, X., Li, Y., Akula, V., Yan, G., Tao, R., 2015. Gaining competitive intelligence from social media data: evidence from two largest retail chains in the world. Ind. Manag. Data Syst.
He, W., Wang, F.K., Akula, V., 2017. Managing extracted knowledge from big social media data for business decision making. J. Knowl. Manag.
He, W., Zha, S., Li, L., 2013. Social media competitive analysis and text mining: a case study in the pizza industry. Int. J. Inf. Manag. 33, 464–472. https://doi.org/10.1016/j.ijinfomgt.2013.01.001.

Henseler, J., Ringle, C.M., Sarstedt, M., 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J. Acad. Mark. Sci. 43, 115–135. https://doi.org/10.1007/s11747-014-0403-8.
Henseler, J., Ringle, C.M., Sinkovics, R.R., 2009. The use of partial least squares path modeling in international marketing, in: New Challenges to International Marketing. Emerald Group Publishing Limited.
Hoyle, R.H., 1995. Structural Equation Modeling: Concepts, Issues, and Applications. SAGE.
Huang, X., Soutar, G.N., Brown, A., 2004. Measuring new product success: an empirical investigation of Australian SMEs. Ind. Mark. Manag. 33, 117–123. https://doi.org/10.1016/S0019-8501(03)00034-8.
Itani, O.S., Agnihotri, R., Dingus, R., 2017. Social media use in B2b sales and its impact on competitive intelligence collection and adaptive selling: examining the role of learning orientation as an enabler. Ind. Mark. Manag. 66, 64–79.
Jin, T., Bouthillier, F., 2007. What do competitive intelligence professionals do? A pilot study. CAIS/ACSI. https://doi.org/10.29173/cais219.
Juhari, A.S., 2009. Evaluation of Competitive Intelligence Software for MSC-status Small and Medium-Sized Enterprises in Malaysia. Loughborough University (Thesis).
Kahaner, L., 1997. Competitive Intelligence: How To Gather Analyze And use Information To Move your Business To The Top. Simon and Schuster.
Kaplan, A.M., Haenlein, M., 2010. Users of the world, unite! The challenges and opportunities of social media. Bus. Horiz. 53, 59–68. https://doi.org/10.1016/j.bushor.2009.09.003.
Kietzmann, J.H., Hermkens, K., McCarthy, I.P., Silvestre, B.S., 2011. Social media? Get serious! Understanding the functional building blocks of social media. Bus. Horiz. 54, 241–251. https://doi.org/10.1016/j.bushor.2011.01.005. SPECIAL ISSUE: Social Media.
Kim, D., Basu, C., Naidu, G.M., Cavusgil, E., 2011. The innovativeness of Born-Globals and customer orientation: learning from Indian Born-Globals. J. Bus. Res. 64, 879–886. https://doi.org/10.1016/j.jbusres.2010.09.008.
Kline, R.B., 2015. Principles and Practice of Structural Equation Modeling, 4th ed. Guilford Publications.
Kock, N., 2015. Common method bias in PLS-SEM: a full collinearity assessment approach: media & communications Journal Article | IGI Global.
Kock, N., Lynn, G., 2012. Lateral collinearity and misleading results in variance-based SEM: an illustration and recommendations (SSRN Scholarly Paper No. ID 2152644). Social Science Research Network, Rochester, NY.
Kogut, B., Zander, U., 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. Organ. Sci. 3, 383–397. https://doi.org/10.1287/orsc.3.3.383.
Larson, D., Chang, V., 2016. A review and future direction of agile, business intelligence, analytics and data science. Int. J. Inf. Manag. 36, 700–710. https://doi.org/10.1016/j.ijinfomgt.2016.04.013.
Lau, K.N., Lee, K.H., Ho, Y., 2005. Text mining for the hotel industry. Cornell Hotel Restaur. Adm. Q. 46, 344–362. https://doi.org/10.1177/0010880405275966.
Leonard-Barton, D., 1992. Core capabilities and core rigidities: a paradox in managing new product development. Strateg. Manag. J. 13, 111–125. https://doi.org/10.1002/smj.4250131009.
Leonardi, P.M., Vaast, E., 2016. Social media and their affordances for organizing: a review and agenda for research. ANNALS 11, 150–188. https://doi.org/10.5465/annals.2015.0144.
López-Robles, J.R., Otegi-Olaso, J.R., Porto-Gomez, I., Gamboa-Rosales, H., Gamboa-Rosales, N.K., 2020. Understanding the intellectual structure and evolution of competitive intelligence: a bibliometric analysis from 1984 to 2017. Technol. Anal. Strateg. Manag. 32, 604–619. https://doi.org/10.1080/09537325.2019.1686136.
Luu, T., 2014. Knowledge sharing and competitive intelligence. Mark. Intell. Plann. 32, 269–292. https://doi.org/10.1108/MIP-05-2013-0077.
Malhotra, Y., 2005. Integrating knowledge management technologies in organizational business processes: getting real time enterprises to deliver real business performance. J. Knowl. Manag. 9, 7–28. https://doi.org/10.1108/13673270510582938.
Marshall, G.W., Moncrief, W.C., Rudd, J.M., Lee, N., 2012. Revolution in sales: the impact of social media and related technology on the selling environment. J. Pers. Sell. Sales Manag. 32, 349–363. https://doi.org/10.2753/PSS0885-3134320305.
Meel, P., Vishwakarma, D.K., 2020. Fake news, rumor, information pollution in social media and web: a contemporary survey of state-of-the-arts, challenges and opportunities. Expert Syst. Appl. 153, 112986 https://doi.org/10.1016/j.eswa.2019.112986.
Meredith, R., O'Donnell, P., 2011. A framework for understanding the role of social media in business intelligence systems. J. Decis. Syst. 20, 263–282. https://doi.org/10.3166/jds.20.263-282.
Montaquila, J.M., Godwin, C.N., 2016. Personnel security and open source intelligence: employing social media analytics in pre-employment screening and selection. J. Inf. Priv. Secur. 12, 145–159. https://doi.org/10.1080/15536548.2016.1213997.
Ngamkroeckjoti, C., Speece, M., 2008. Technology turbulence and environmental scanning in Thai food new product development. Asia Pac. J. Mark. Logist. 20, 413–432. https://doi.org/10.1108/13555850810909731.
Ngussa, B.M., Fitriyah, F.K., Diningrat, S.W.M., 2020. Correlation between Facebook use, mental health and learning engagement. Turk. Online J. Distance Educ. 22, 229–245. https://doi.org/10.17718/tojde.849912.
Nguyen, B., Yu, X., Melewar, T.C., Chen, J., 2015. Brand innovation and social media: knowledge acquisition from social media, market orientation, and the moderating role of social media strategic capability. Ind. Mark. Manag. 51, 11–25. https://doi.org/10.1016/j.indmarman.2015.04.017.
Nunes, M., Correia, J., 2013. Improving trust using online credibility sources and social network quality in P2P marketplaces. In: Proceedings of the 8th Iberian Conference on Information Systems and Technologies (CISTI), pp. 1–4. Presented at the 2013 8th Iberian Conference On Information Systems and Technologies (CISTI).
OECD, 2019. OECD SME and Entrepreneurship Outlook 2019. OECD. https://doi.org/10.1787/34907e9c-en.
Oubrich, M., 2011. Competitive intelligence and knowledge creation - outward insights from an empirical survey. J. Intell. Stud. Bus. 1 https://doi.org/10.37380/jisib.v1i1.18.
Pinsonneault, A., Kraemer, K., 1993. Survey research methodology in management information systems: an assessment. J. Manag. Inf. Syst. 10, 75–105. https://doi.org/10.1080/07421222.1993.11518001.
Porter, M.E., 1980. Industry structure and competitive strategy: keys to profitability. Financ. Anal. J. 36, 30–41. https://doi.org/10.2469/faj.v36.n4.30.
Prescott, J.E., 1995. The evolution of competitive intelligence. Rev. Intel. Compet. 2 https://doi.org/10.24883/ric.v2i2.45.
Ramanathan, U., Subramanian, N., Parrott, G., 2017. Role of social media in retail network operations and marketing to enhance customer satisfaction. Int. J. Oper. Prod. Manag. 37, 105–123. https://doi.org/10.1108/IJOPM-03-2015-0153.
Ranjan, J., Foropon, C., 2021. Big data analytics in building the competitive intelligence of organizations. Int. J. Inf. Manag. 56, 102231 https://doi.org/10.1016/j.ijinfomgt.2020.102231.
Riera, C., Iijima, J., 2019. The role of IT and organizational capabilities on digital business value. Pac. Asia J. Assoc. Inf. Syst. 11.
Rindfleisch, A., Malter, A.J., Ganesan, S., Moorman, C., 2008. Cross-sectional versus longitudinal survey research: concepts, findings, and guidelines. J. Mark. Res. 45, 261–279. https://doi.org/10.1509/jmkr.45.3.261.
Ringle, C.M., Wende, S., Becker, J.M., 2015. SmartPLS 3 [computer software]. SmartPLS GmbH.
Ross, P., McGowan, C., Styger, L., 2012. A comparison of theory and practice in market intelligence gathering for Australian micro-businesses and SMEs (SSRN Scholarly Paper No. ID 2253691). Social Science Research Network, Rochester, NY. 10.2139/ssrn.2253691.
Rothberg, H.N., Erickson, G.S., 2005. From Knowledge to Intelligence: Creating Competitive Advantage in the Next Economy. Routledge.
Saayman, A., Pienaar, J., de Pelsmacker, P., Viviers, W., Cuyvers, L., Muller, M., Jegers, M., 2008. Competitive intelligence: construct exploration, validation and equivalence. Aslib Proc. 60, 383–411. https://doi.org/10.1108/00012530810888006.
Sammon, W.L., Kurland, M.A., Spitalnic, R., 1984. Business competitor intelligence: methods for collecting, organizing and using information. New York.
SCIP, Society of C.I.P., 2015. Competitive & market intelligence topic hub [WWW Document]. Society of Competitive Intelligence Professionals. URL https://www.scip.org/page/CI-MI-Basics-Topic-Hub (accessed 3.5.21).
Scuotto, V., Del Giudice, M., Carayannis, E.G., 2017. The effect of social networking sites and absorptive capacity on SMES' innovation performance. J. Technol. Transf. 42, 409–424. https://doi.org/10.1007/s10961-016-9517-0.
Segars, A.H., Grover, V., 1999. Profiles of strategic information systems planning. Inf. Syst. Res. 10, 199–232. https://doi.org/10.1287/isre.10.3.199.
Sharma, A., 1999. Central dilemmas of managing innovation in large firms. Calif. Manag. Rev. 41, 146–164. https://doi.org/10.2307/41166001.
Sharp, S., 2009. Competitive Intelligence Advantage: How to Minimize Risk, Avoid Surprises, and Grow your Business in a Changing World. John Wiley & Sons.
Singh, A., Shukla, N., Mishra, N., 2018. Social media data analytics to improve supply chain management in food industries. Transp. Res. Part E Logist. Transp. Rev. 114, 398–415. https://doi.org/10.1016/j.tre.2017.05.008.
Soni, G., Mangla, S.K., Singh, P., Dey, B.L., Dora, M., 2021. Technological interventions in social business: mapping current research and establishing future research agenda. Technol. Forecast. Soc. Chang. 169, 120818 https://doi.org/10.1016/j.techfore.2021.120818.
Straub, D., Boudreau, M.C., Gefen, D., 2004. Validation guidelines for is positivist research. Commun. Assoc. Inf. Syst. 13, 380–427. https://doi.org/10.17705/1CAIS.01324.
Teece, D.J., 2018. Business models and dynamic capabilities. Long Range Plann. 51, 40–49. https://doi.org/10.1016/j.lrp.2017.06.007.
Teece, D.J., 2007. Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. Strateg. Manag. J. 28, 1319–1350. https://doi.org/10.1002/smj.640.
Teece, D.J., Pisano, G., Shuen, A., 1997. Dynamic capabilities and strategic management. Strateg. Manag. J. 18, 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID−SMJ882>3.0.CO;2-Z.
Tenenhaus, M., Vinzi, V.E., Chatelin, Y.M., Lauro, C., 2005. PLS path modeling. Comput. Stat. Data Anal. 48, 159–205.
Thomas, J.B., Trevino, L.K., 1993. Information processing in strategic alliance building: a multiple-case approach*. J. Manag. Stud. 30, 779–814. https://doi.org/10.1111/j.1467-6486.1993.tb00326.x.
Toker, A., Seraj, M., Kuscu, A., Yavuz, R., Koch, S., Bisson, C., 2016. Social media adoption: a process-based approach. J. Organ. Comput. Electron. Commer. 26, 344–363. https://doi.org/10.1080/10919392.2016.1228361.
Tsitoura, N., Stephens, D., 2012. Development and evaluation of a framework to explain causes of competitive intelligence failures [WWW Document]. URL http://informationr.net/ir/17-2/paper521.html (accessed 3.5.21).
Vedder, R.G., Vanecek, M.T., Guynes, C.S., Cappel, J.J., 1999. CEO and CIO perspectives on competitive intelligence. Commun. ACM 42, 108–116. https://doi.org/10.1145/310930.310982.
Vinzi, V.E., Trinchera, L., Amato, S., 2010. PLS path modeling: from foundations to recent developments and open issues for model assessment and improvement. Handbook of Partial Least Squares. Springer, pp. 47–82.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J., Dubey, R., Childe, S.J., 2017. Big data analytics and firm performance: effects of dynamic capabilities. J. Bus. Res. 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009.

Wang, C.H., Borges, L.A.J., 2013. Does competitive intelligence matter? An anthropological way of thinking. Int. J. Bus. Anthropol. 4, 76–84. https://doi.org/10.33423/ijba.v4i2.1152.

Wieneke, A., Lehrer, C., 2016. Generating and exploiting customer insights from social media data. Electron. Mark. 26, 245–268. https://doi.org/10.1007/s12525-016-0226-1.

Xu, P., Kim, J., 2014. Achieving dynamic capabilities with business intelligence. In: Proceedings of the Pacific Asia Conference on Information Systems (PACIS), p. 11.

Yap, C.S., Rashid, M.Z.A., 2011. Competitive intelligence practices and firm performance. Libri Int. J. Libr. Inf. Serv. 61, 175–189. https://doi.org/10.1515/libr.2011.015.

Zahra, S.A., George, G., 2002. The net-enabled business innovation cycle and the evolution of dynamic capabilities. Inf. Syst. Res. 13, 147–150. https://doi.org/10.1287/isre.13.2.147.90.

Zanasi, A., 1998. Competitive intelligence through data mining public sources. Compet. Intell. Rev. 9, 44–54. https://doi.org/10.1002/(SICI)1520-6386(199801/03)9:1<44::AID−CIR8>3.0.CO;2-A.

Zeng, J., Chan, C., Fu, K., 2017. How social media construct "truth" around crisis events: weibo's rumor management strategies after the 2015 Tianjin Blasts. Policy Internet 9, 297–320. https://doi.org/10.1002/poi3.155.

Zhan, Y., Han, R., Tse, M., Ali, M.H., Hu, J., 2021. A social media analytic framework for improving operations and service management: a study of the retail pharmacy industry. Technol. Forecast. Soc. Chang. 163, 120504 https://doi.org/10.1016/j.techfore.2020.120504.

Zollo, M., Winter, S.G., 2002. Deliberate learning and the evolution of dynamic capabilities. Organ. Sci. 13, 339–351. https://doi.org/10.1287/orsc.13.3.339.2780.

Abdeslam Hassani is a professor at the Department of Marketing and Information Systems, Business School, Université de Québec à Trois-Rivières, Canada. Abdeslam is member of IntelliLab, a research group on emerging digital technologies. He is also member of INRPME a research institute on the SMEs at Université de Québec à Trois-Rivières. Ha was director of research in intelligence and innovation within Merkur company at Sherbrooke, Canada. Abdeslam participated and published in selected international congresses such as ASAC, IAMOT, and he published in journals as JISB. Abdeslam is interested in many fields of research as competitive intelligence, innovation performance, absorptive capacity, especially in SMEs context.

Elaine Mosconi is an Associate Professor at the Université de Sherbrooke, Business School, Department of Information Systems and Quantitative Methods, Sherbrooke, Canada. Elaine is the head of IntelliLab, a research group on emerging digital technologies in the context of the 4th Industrial Revolution and of the center of Excellence for Innovative Manufacturing Companies. She collaborates with many multidisciplinary research groups, such as Collaborative Research Network on Supply Chain (SC4), Collaborative Robotics on Manufacturing (CoRoM), Research Pole on Business Intelligence (PRISME) and the WAIM. Network (Work in age of Intelligent Machine). She has worked as a researcher and consultant knowledge management and information systems. Professor Elaine has coauthored papers published in peer-reviewed journals and selected conferences as AoM, HICSS and ECIS. Her current research interests are related to digital transformation, collaborative innovation, business intelligence, Industry 4.0 and decision performance, especially in manufacturing sector context.