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OF BI RESEARCH: A TALE OF TWO COMMUNITIES

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ABSTRACT

The Business intelligence (BI) literature is in flux, yet the knowledge about its varying theoretical roots remains elusive. This state of affairs draws from two different scientific communities (informatics and business) that have generated multiple research streams, which duplicate research, neglect each other's contributions, and overlook important research gaps. In response, we structure the BI scientific landscape and map its evolution to offer scholars a clear view of where research on BI stands and the way forward. For this endeavor, we systematically review articles published in top-tier ABS journals and identify 120 articles covering 35 years of scientific research on BI. We then run a co-citation analysis of selected articles and their reference lists. This yields the structuring of BI scholarly community around six research clusters: Environmental Scanning (ES), Competitive Intelligence (CI), Market Intelligence (MI), Decision Support (DS), Analytics Technologies (AT), and Analytics Capabilities (AC). The Co-citation network exposed overlapping and divergent theoretical roots across the six clusters and permitted mapping the evolution of BI research following two pendulum swings. Our article contributes by 1) structuring the theoretical landscape of BI research, 2) deciphering the theoretical roots of BI literature, 3) mapping the evolution of BI scholarly community, and 4) suggesting an agenda for future research.

Business Intelligence, Competitive Intelligence, Market Intelligence, Decision Support Systems, Big Data, Analytics.

INTRODUCTION

The extant body of knowledge on Business Intelligence (BI), because of its fragmented state, has overlooked to map the BI literary landscape and subsequently identify the lack of cross-disciplinary relationships between the informatics and business communities. Because of ontological and epistemological discrepancies, each of these communities produced disjointed BI research that uses a myriad of concepts interchangeably with BI and nurtured a particular focus on the needs pertaining to the operational and tactical levels. We refer to this divergence of research interests and progress as a dichotomy between the business and informatics communities that weave the strands of the BI scientific landscape and inhibits a comprehensive view of BI that accounts for cross-disciplinary research gaps.

Prior BI research examines the impact of environmental (Boyd & Fulk, 1996; Ebrahimi, 2000), organizational (Qiu, 2008; Ramakrishnan, Jones & Sidorova, 2012), managerial antecedents (Cho, 2006; Elbashir, Collier, & Sutton, 2011), and top executives' goal orientation and personalities (Pryor, Holmes, Webb, & Liguori, 2019) on business intelligence quality and value. Besides, the research draws a causation link between BI and indicators of operational efficiency such as price optimization (Abramson, Currim, & Sarin, 2005), sales optimization (Cheung & Li, 2012; Heinrichs & Lim, 2003; Hughes, Le Bon, & Rapp, 2013), and innovation (Slater & Narver, 2000; Tanev & Bailetti, 2008; Trim & Lee, 2008). Unfortunately, this line of thinking yields a disparate focus on BI: on the one hand, some scholars theorize BI as a capability for market analysis

(Fleisher, Wright, & Allard, 2008; Li, Shue, & Lee, 2008; Qiu, 2008), value creation (Grover, Chiang, Liang, & Zhang, 2018), and decision making (Merendino et al., 2018; Constantiou, Shollo, & Vendelø, 2019); other scholars conceptualize it as a prop (Wang, Kung, Wang, & Cegielski, 2018), or a model (Gupta & George, 2016; Bricni et al., 2017) for data variety and velocity (Ghasemaghaei & Calic, 2020).

Such disjointed theoretical progress motivates this systematic literature review of 120 articles published in top-tier ABS journals from 1985 to 2020. We thereby seek to: a) structure the BI scholarly community around six research clusters: Environmental Scanning (ES), Competitive Intelligence (CI), Market Intelligence (MI), Decision Support (DS), Analytics Technologies (AT), and Analytics Capabilities (AC); b) investigate the theoretical roots of six clusters that form the BI research; c) map the evolution of BI literature; and d) suggest an integrative research agenda of the informatics and business communities with clear research gaps. We structure the rest of the article as follows. The first section presents the review process and co-citation analysis. The second section explains the theoretical roots of the six clusters that compose the body of knowledge on BI. The third section traces the evolution of its body of knowledge. The paper concludes with a future research agenda.

METHOD

Following (Tranfield, Denyer, & Smart, 2003), we identified keywords based on previous reviews on BI. Boolean operators (“AND” and “OR”), and asterisk wildcard were used to concatenate keywords and generate query strings. We then systematically searched four databases: ABI/Inform, EBSCO Academic search elite, EBSCO business premier, and Emerald journals for

relevant literature. We followed two exclusion/inclusion criteria to select our final sample: acceptability and relevance (Robey, & Dalebout, 1998). Acceptability limited this review to top-tier journal articles (Vogel, 2012) covering the cross-disciplinary nature of BI research between 1985 and 2020 to include early landmark works of Environmental Scanning (ES) and Competitive Intelligence (CI) such as (El Sawy, 1985; Ghoshal & Kim, 1986). Passing our relevance criteria meant that each of the 120 articles of our final sample carried a theoretical scaffolding in the literary landscape of BI. Appendix 1 presents our search strings and maps the systematic research process we followed to reach our sample of 120 articles.

To reduce subjectivity and better comprehend the structure of BI research and ensure further rigor, we opted for an author co-citation analysis as the sole bibliometric method of this paper. By so doing, we sought to 1) analyze each time a pair of authors was cited together (Acedo, Barroso, & Galan, 2006; Di Stefano, Peteraf, & Verona, 2010; Galvagno & Dalli, 2014; Vogel & Güttel, 2013), and 2) identify contributors holding similar thoughts and boundary spanners based on the selected articles and their lists of references (Nerur, Rasheed, & Natarajan, 2008). VOS viewer software (Van Eck, Waltman, Dekker, & van den Berg, 2010; Waltman, Van Eck, & Noyons, 2010) orchestrated the co-citation analysis through the VOS mapping technique (Van Eck et al., 2010) that follows several parameters to generate the final network of research landscape. Initially, we adopted a conservative analysis that generated two diverging scholarly communities (informatics-oriented vs business enthusiasts) whose theoretical scrutiny implied a further breakdown of the aforementioned communities resulting in six research clusters displayed in the following section in a graphic hassle-free map.

THE THEORETICAL ROOTS OF BI RESEARCH

The bibliometric analysis of articles along their references generated a co-citation network (Figure 1) displaying a BI research comprising six clusters led by two scientific communities: business and informatics. The latter community produced 58 publications: 16 articles from the Analytics Capabilities (AC) cluster, 18 papers under the Decision Support (DS) cluster, and 24 publications by the Analytics Technologies (AT) cluster. The business community generated 62 articles dispersed across its three streams. Whereas the Environmental Scanning (ES) cluster and the Competitive Intelligence (CI) clusters each generated 26 publications; 10 articles made up the Market Intelligence (MI) cluster. As shown in Figure 1, the BI scholarly community contains five interrelated clusters and a maverick constellation of authorships around technical aspects of BI, i.e., the Analytics Technologies (AT) cluster. Paradoxically, this same cluster springs from the same community spawning the Analytics Capabilities (AC) and Decision Support (DS) clusters that both seem to nurture ties with two other clusters of business community: Competitive Intelligence (CI) and Environmental scanning (ES). Figure 1 also displays these links as citations of well-known strategy scholars like Hambrick, Mintzberg, Porter, Eisenhardt, Whittington. Unfortunately, this research tradition faded away during the early 2000s when the new Analytics Technologies (AT) cluster took over the dominance of BI research. In what follows, we attempt to bring to light the theoretical underpinnings of BI literature by depicting the theoretical grounds of six clusters.

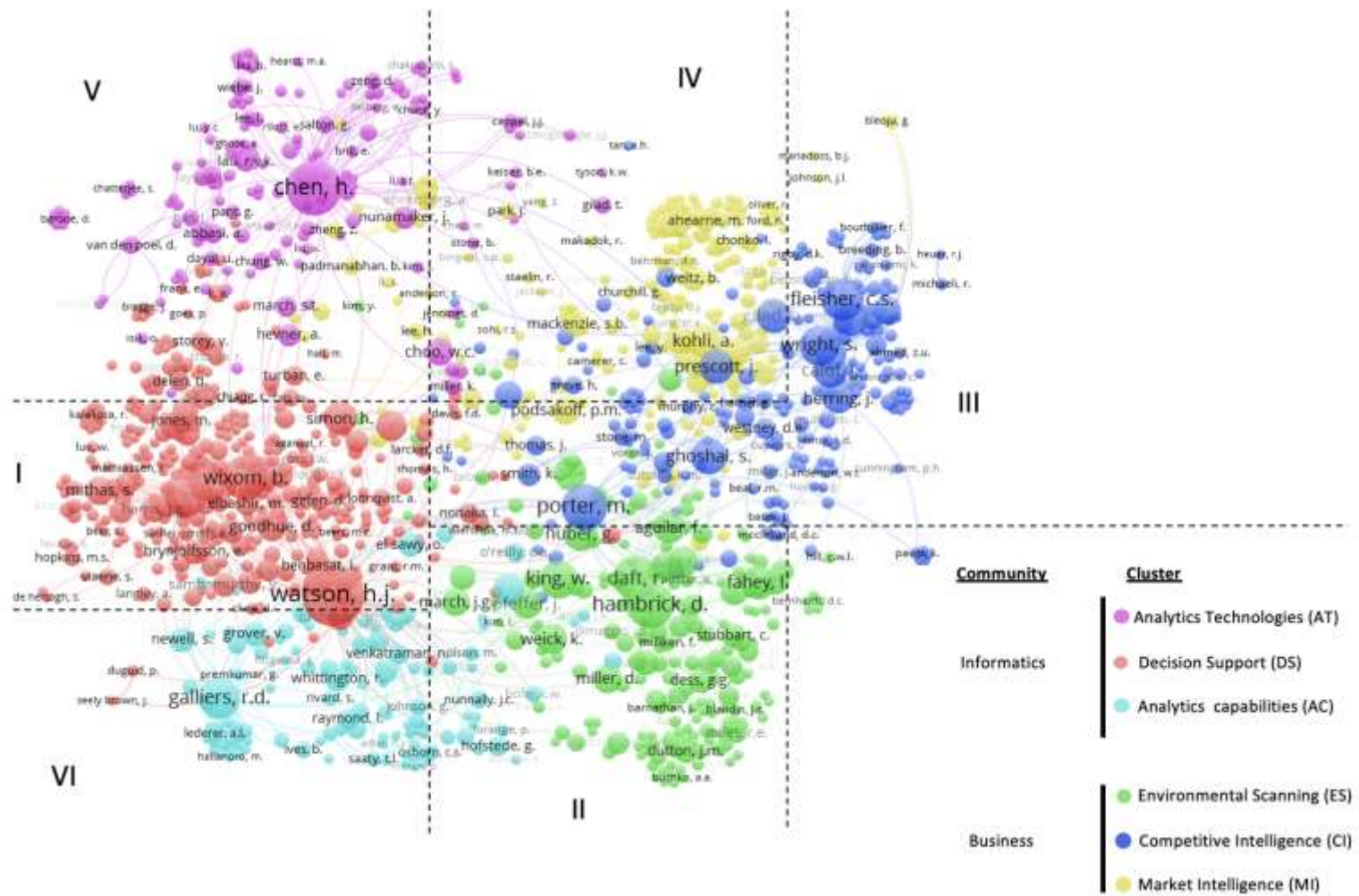


Figure 1. Quantitative identification of the BI research clusters

The Environmental Scanning (ES) cluster: S-C-P paradigm vs Organizational theory

Conceptualized as a formal constituent of the strategic management process (Aguilar, 1967; Peyrot, Doren, Allen, & Childs, 1996), environmental scanning attracted scholars' attention and produced a significant batch of conceptual and empirical papers (e.g., Daft, Sormunen, & Parks, 1988; Yasai-Ardekani & Nystrom, 1996; May, Stewart, & Sweo, 2000) that adhere to the Structure-Conduct-Performance (S-C-P) paradigm (Mason, 1939). Thus, the dominant school of thought in the Environmental Scanning (ES) cluster (Quadrant 2, Figure 1) views firms' actions as rooted in the structure of their respective environment that constrain their behavior and influences their performance (Brownlie, 1994; Peyrot et al., 1996). In this context, scholars with scaffolding in industrial economics formalized the concept as an activity in the strategy process for proactively scanning a rapidly shifting environment for strategic opportunities (Cho, 2006; Fabbe-Costes, Christine, Margaret, & Taylor, 2014; Lau, Liao, Wong, & Chiu, 2012 ; Robinson & Simmons, 2017; Reinmoeller & Ansari, 2016).

This rationale motivated the dominant theoretical strand of environmental scanning research and pictured it as the first link activity whereby firms can comprehend their industry and remain on top of any changes (Hambrick, 1981). Contemporaneously, early remarks of environmental scanning in Cyert and March's (1963) theory of organizational behavior motivated another research stream that nurtured a particular interest in the effects of environmental elements on the scanning dimensions: scope and frequency (Peyrot et al., 1996; Yasai-Ardekani & Nystrom, 1996). This research stream focused on the notions of instability and complexity as the main constituents of environmental uncertainty (Thompson, 1967; Lawrence & Lorsch, 1967; Duncan, 1972; Peyrot et al., 1996), decomposed the environment into task and remote, and suggested that the structures

of both constituents dictate the focus of scanning activity (Thompson, 1967; Peyrot et al., 1996). This latter is often pegged to top executives and their goals orientations, cognition, character, or values (Pryor et al., 2019) following upper echelons theory (Hambrick, 2007).

The Competitive Intelligence (CI) cluster: Managerial heuristics and atheoretical practice

In response to the shortcomings of environmental scanning (e.g. failure to deliver competitive advantage), the CI research imported the concept of competitor analysis to the intelligence equation, following Porter's (1980) seminal work (Peyrot et al., 1996). The common theme across publications in the CI cluster (Quadrant 3, Figure 1) is the use of eclectic definitions of intelligence concept that fall into two research streams: CI as a product and CI as a process. The former regards CI as the final intelligence or knowledge delivered to the business user (Chen, Chau, & Zeng, 2002; Xu, Liao, Li, & Song, 2011; Zheng, Fader, & Padmanabhan, 2012); the latter considers it a sequential activity through which it funnels intelligence to support organizational objectives (Dishman & Calof, 2008; Liu & Wang, 2008; Wright et al., 2009) and whose budgeting enhances organizational vigilance against environment uncertainty (Opait, Bleoju, Nistor, & Capatina, 2016).

As a product, the generation of ready-to-use CI from open or human sources occupies the center of the debate. As a process, attention tilts toward the transformation of gained data into usable intelligence. Although some scholars root the competitive intelligence in the marketing research (Schollhammer, 1994; Dishman & Calof, 2008), we found ourselves inclined to agree with others suggesting that competitive intelligence encompasses the entire business biosphere (Dishman & Calof, 2008). This research stream stressed the necessity of analysis, yet stayed prescriptive mostly with insignificant theoretical grounds except for Porter's five forces and SWOT analysis that,

although rooted in strategic management, came to the fore for their high straightforwardness and low theoretical complexity. Although some works by some well-known scholars of this cluster (Ghoshal & Westney, 1991) places competitive intelligence at the heart of the strategic decision-making process, it does so in a manager friendly manner that highlights the prowess of the SWOT analysis as a device for competitors' profiling and benchmarking.

The Market Intelligence (MI) cluster: Market research vs social network theory

The market intelligence body of knowledge (Quadrant 4, Figure 1) accorded full attention to the external intelligence that carries competitive value (e.g. customers' needs, and competitors' distinctive competence) (Day, 1994; Kohli & Jaworski, 1990; Narver & Slater, 1990; Slater & Narver, 2000). In doing so, this stream generated a research driven by operational effectiveness rather than strategy: gaining market intelligence and fostering best ways to meet or exceed market demands and expectations (Day, 1994; Slater & Narver, 2000). This research is grounded in Nielsen's market measures and the Dirichlet literature that offer market enthusiasts a myriad of competitive indicators (e.g. market share, market penetration, etc.) to test the firm's operational effectiveness (Farris, Bendle, Pfeifer, & Reibstein, 2006; Zheng et al., 2012). Strangely enough, this research practice pursued its focus in an outright overlooking of the organizational level of intelligence, particularly the focal firm's resources and distinctive competence.

Two research stands within the Market intelligence cluster exhibited an interest in the organizational and individual levels of intelligence. The first stream explored the dissemination and exploitation of gained intelligence relying on social exchange theory (Homans, 1961), the role of hierarchical relationships (Huber & McDaniel, 1986), power and politics in the relationships

between intelligence sender and receiver (Maltz & Kohli, 1996), and disaggregated product-firm-market level intelligence to yield firms better resource allocation (Kumar, Saboo, Agarwal, & Kumar, 2020). The second stream's attention was directed to boundary spanners' activities vis-à-vis the collection and usage of intelligence and drew from both the cognitive selling paradigm (e.g. Kahaner, 1997; Rothberg & Erickson, 2005; Fleisher et al., 2008; Rapp, Agnihotri, & Baker, 2011; Mariadoss, Milewicz, Lee, & Sahaym, 2014), and expectancy theory (e.g. Tyagi, 1985; Sujan, 1986; Le Bon & Merunka, 2006).

The Decision Support (DS) cluster: When strategic management and organization theory meet information systems

Originating from works on computerized Decision Support Systems (DSS) and Executive Information Systems (ESS), the extant literature propelled this cluster toward supporting the decision-making process via a cross-organizational integrated technology and customized user interfaces (Volonino, Watson, & Robinson, 1995; Walters, Jiang, & Klein, 2003). The ubiquitous argument across the Decision Support Systems cluster (DSS) (Quadrant 1, Figure 1) research is the alignment of organizational structure and technology with the environment as a key element in achieving competitive advantage or what some refer to as survival if one substitutes firms with organisms (Huber, 1984). This logic is grounded in contingency theory (Burns & Stalker, 1961; Lawrence & Lorsch, 1967) and systems theory (Miller, 1972; Boulding, 1981). Other scholars also voiced the Structure-Conduct-performance (SCP) paradigm and Chandler's "structure follows strategy" as a theoretical tutelage behind this cluster's focus on structure (Huber, 1984; Volonino et al., 1995). The decision support narrative finds theoretical grounds in the Gorry and Morton framework (1989) and Simon's model of decision-making (1947) that follows a three phase

iterative sequence of gathering intelligence, building options, and selecting the best-case scenario (Aversa, Cabantous, & Haefliger, 2018; Arnott, Lizama, & Song, 2017).

Another prevalent thinking across this literature is the premise that technology is a material that is transferable and controllable (Gherardi, 2000; Petrini, & Pozzebon, 2009). This requires flat organizations with decentralized decision-making and centralized control (Drucker, 1989; Volonino et al., 1995). This argument stands on two legs: organizational ecology (Hannan & Freeman, 1977; Carroll, 1990) determines that in dynamic environments firms' restructuring follows the high performers, and transaction cost economics (Williamson, 1983) that associates high control with a low number of transactions and transaction costs (e.g. technologies and associated costs) (Volonino et al., 1995).

The Analytics Technologies (AT) cluster: An ad-hoc technical research

In the early nineties, BI emerged as a term to coin the technologies at the core of the Decision Support Systems (DSS) and Executive Information Systems (EIS) and nurtured scholars' desire to bridge the gap between the business user and business analytics technologies. This state of affairs lured researchers to focus on reducing the time cycle from data collection to knowledge impartment via a casual visualization that simplifies the quantitative displays of data (Kohavi, Rothleder, & Simoudis, 2002). Web 2.0 and the technological advancement of the new millennium engaged scholars in a continuous development of new ways of codifying structured and unstructured data yielding research that resembles more a benchmark of commercial technologies with in-house developed ones or an update of some technical flaws pegged to existing applications.

A common trend of this cluster (Quadrant 5, Figure 1) is the ad hoc upgrades of the intelligence architecture following the functional linguistic theory or sentiment analysis (Abbasi & Chen, 2008; Lau et al., 2012). Besides, an evaluation of the proposed prototypes based on analytic hierarchy process (AHP) (Lin, Tsai, Shiang, Kuo, & Tsai, 2009), or against commercial engines seems prevalent (Chau, Shiu, Chan, & Chen, 2007; Chung, Chen, Nunamaker, & Nunamaker Jr, 2005; Srivastava & Cooley, 2003). Hence, our nomenclature of this cluster as ad hoc for it represents research in constant flux that shadows a commercial rationale of tracking enterprise intelligence infrastructure, detect faults, correct algorithms and upgrade technologies (Lin et al., 2009). This tradition also characterizes another stream of research within this cluster that develops indices or models to test and test the analytical capability (Gupta & George, 2016; Bricni et al., 2017) or predictive sensing (Hallin, Andersen, & Tveterås, 2017) of BI against software development systems such as ISO 25000 (ISO, 2014) or models based on Fuzzy TOPSIS techniques (Rouhani, Ghazanfari, & Jafari, 2012).

The Analytics Capabilities (AC) cluster: Practice theory vs Knowledge-based view

Contrary to the tradition of Informatics research where Business Intelligence enjoys a supportive role in decision-making, the analytics capability (AC) cluster (Quadrant 6, Figure 1) broadens BI impact to comprise all organizational processes and the knowledge work and business value in particular (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Bordeleau, Mosconi, & de Santa-Eulalia, 2020; Shollo & Galliers, 2015). The first stream of this cluster builds on the knowledge based view (Grant, 1996), dynamic capabilities (Teece, 2007) and organizational learning ambidexterity (Jansen, Tempelaar, van den Bosch, & Volberda, 2009) view knowledge as a rare and valuable resource that yields competitive advantage once leveraged (Côte-Real,

Oliveira, & Ruivo, 2017; Côte-Real, Ruivo, & Oliveira, 2020; Côte-Real, Ruivo, Oliveira, & Popovič, 2019). The BI value stems from its ability to enable this leveraging that can benefit organizational learning and culture (Akter et al., 2016; Bordeleau et al., 2020), and build up firms' dynamic capabilities (Mikalef, Boura, Lekakos, & Krogstie, 2019; Wamba et al., 2017)

The second stream of this cluster rejects the previously held view of knowledge as an objectified commodity (Gherardi, 2000), and embraces the sociological practice lens that equates knowledge with practice and positions the practitioner and their micro actions at the heart of knowledge creation (Cetina, Schatzk, & Eike Von, 2005; Peppard, Galliers, & Thorogood, 2014). Researchers adopt the practice theory to explore the human interactions that involve the tacit and dynamic process of knowledge creation occurring at the intersection of the social and the physical (Cook & Brown, 1999; Shollo & Galliers, 2015). In this vein, BI becomes an active facilitator of the participatory process of organizational knowing that comprises sense making, knowledge creation, and decision-making (Choo, 2002; Shollo & Galliers, 2015). In parallel, knowing emanates from the participant's experiences, interactions, actions, and contestations (Kolb & Kolb, 2005; Shollo & Galliers, 2015), and evolves and transforms as participants engage in the practice of knowing (Orlikowski, 2002).

THE EVOLUTION OF BI RESEARCH

Early references of intelligence as an activity to gain knowledge about the environment are omnipresent in the Environmental Scanning cluster (ES) where reside the roots of BI. Scholars in this cluster adopt an outside-in perspective that pictures firms as biological organisms whose actions are often constrained by their external environments (Brownlie, 1994). This implies that

organizations should constantly monitor their respective environments to ensure the detection of plausible alterations susceptible of jeopardizing their competitive advantage. This logic fueled a proliferation of studies examining both the corporate practice of environmental scanning and the variables influencing its use (Jennings & Lumpkin, 1992). Since most companies scan their respective environments the effective response to threats and opportunities arises as the ultimate challenge (Huber, 1990). Once detected, signals at the periphery of the firm entail a proper evaluation and interpretation. Only then, the environmental scanning can serve as a weapon to support managerial action (Fabbe-Costes et al., 2014).

In response, Porter's influential book (1980) framed the analysis arena along five forces and associated competitor analysis to business strategy (Peyrot et al., 1996). Thenceforth, an avalanche of works depicted the competitor behavior instead of the amorphous boundaries of firms' environment (Peyrot et al., 1996). Inspired by competitor analysis and market research, two new streams joined the environmental scanning cluster: Competitive Intelligence (CI), and Market Intelligence (MI). Under CI, researchers explored corporate CI activities, and prescribed intelligence best practices, whereas MI scholars focused on the consumer as a source of data and salespersons as collectors and disseminators of intelligence (Bernhardt, 1994; Le Bon & Merunka, 2006; Fleisher et al., 2008; Mariadoss et al., 2014).

The careful reader shall notice the outside-in focus of the three clusters (Environmental Scanning (ES), Competitive Intelligence (CI), Market Intelligence (MI)) on the external environment while overlooking data regarding the distinctive competence (Selznick, 1957) of the focal firm. Following this rationale, scholars studied the influence of environmental factors on the scanning

activity such as uncertainty (Hubert & Daft, 1987), complexity (Child, 1972), rate of change (Daft et al., 1988), importance (Aaker, 1983; Pfeffer & Salancik, 1978), culture (Leidner, Carlsson, Elam, & Corrales, 1999), and competitive pressures (Zhu & Kraemer, 2005). Other widespread examples are the share of wallet (Zeithaml, 1988), customer perceived value (Hughes et al., 2013), product development (Lynn, 1998), superior sales growth (Slater & Narver, 2000), and market orientation (Narver & Slater, 1990).

Traditionally, the collection of intelligence was formal or informal through open and human sources. However, with the internet, the intelligence gathering activity faced the challenge of information overload (Chen et al., 2002). This new reality called for a more tailored information allocation system capable of gaining external and internal data (Christen, Boulding, & Staelin, 2009), and signaled the swing of BI research pendulum from an outside-in intelligence collection to an inside-out sophisticated analysis run by computerized decision support systems (DSS) that prepare the requested intelligence for executives (Leidner & Elam, 1993). Such decision aids stimulated the design of Executive Information Systems (EIS) with the purpose of retrieving the information related to internal operations, and the business environment (Turban & Schaeffer, 1987), and gave birth to the Decision Support Systems (DSS) cluster that grew beyond data warehouses (Sen & Sinha, 2005) to encompass the organizational decision-making process (Turban, King, & Lang, 2010).

Nothing captures this stream's orientation better than the organizational factors its scholars shed light upon: managerial heterogeneity (Cho, 2006), experience (Thomas, Litschert, & Ramaswamy, 1991), managerial attitude (Qiu, 2008), absorptive capacity (Elbashir et al., 2011),

problem identification speed (Leidner & Elam, 1995), and extent of analysis (Miller & Friesen, 1980). This stream represented the traditional school of Information Systems (IS) that focuses on the macro-level of organizations and views knowledge as a transferable commodity from the sender to the receiver (Gherardi, 2000; Shollo & Galliers, 2015). Such a simplistic definition of the concept of knowledge combined with the outright overlooking of the human element in knowledge creation, particularly underscored by processes like sensemaking (Weick, 1995), beget the second pendulum swing of the BI research toward practice theory and sociology generating what we dub the Analytics Capabilities (AP) scholarly stream. In short, the AP is nascent prescriptive research that attempts to remodel the Information Systems (IS) research following the practice theory, knowledge-based view, and dynamic capabilities. Scholars tilted their attention toward the micro-level of organizations and introduced concepts enjoy strategizing in IS (Shollo & Galliers, 2015), IS strategy as practice (Peppard et al., 2014), organizational knowing (Choo, 2002; Shollo & Galliers, 2015), BI capability (Akter et al., 2016; Bordeleau et al., 2020; Côte-Real et al., 2017).

Finally, the technologies that the data warehouse deploys to execute queries across a wide range of data (e.g. Extract-Transform-Load (ETL), relational database management system (RDBMS), online analytic processing (OLAP) server) (Chaudhuri, Dayal, & Narasayya, 2011) attracted scholars' interest in their upgrading and prototyping. This theme makes up the Analytics Technologies (AT) cluster that seems to have held sway over the rest of clusters thanks to its heavy technological penchant that seeks to produce turnkey solutions for industries. In sum, the particularity of BI literature rooted in two scientific communities yielded a disjointed research. Hence, the lack of a comprehensive view of BI because of ontological and

epistemological discrepancies between the management and informatics communities that weave the strands of BI research. Unfortunately, while still at an early stage, the BI research cut its umbilical cord with the business community in the late 2000s. Nothing mirrors such a state better than the plummeting contributions of the business community that led the field at the outset of the 2000s. A significant share of contributions belongs to the informatics community with a dominant Analytics Technologies (AT) research, and publications from both the Decision Support (DS) cluster and the Analytics Capabilities (AC) stream. Figure 2 exhibits this state of affairs by assigning the 120 articles to the six research clusters of BI research from 1985 to 2020.

	Up to 2000	2000 - 2005	2005 - 2010	2010 - 2015	2015 - 2020
ES	El sawy (1985) Lenz & Engledow (1986a)/Lenz & Engledow (1986b) Daft et al (1988) Jennings& Lumpkin (1992) Babbar & Rai (1993)/ Lasserre (1993)/ Sawyerr (1993) Brownlie (1994)/Bernhardt (1994) Ardekani & Nystrom(1996)/Lim et al (1996)/ Boyd & Fulk (1996) Elenkov (1997) Ahituv et al (1998) Ebrahimi (2000)/May et al (2000)	Walters et al (2003) Haeciel (2004) Brown (2004)	Chiu (2006) Cju (2008)	Fabbe-Costes et al (2014) Reinmoeller & Ansari (2016)	Pryor et al (2019)
CI	Gilad & Gilad(1986)/Ghoshal & Ki (1986) Prescott & Smith (1987) Ghoshal & Westney (1991) Taylor (1992) Gilad et al (1993) Peyrot et al (1996)	Gordon & Loeb (2001) Peyrot et al (2002) Chen et al (2002) Abramson et al (2005) Wright & Calof (2006)	Fleisher et al (2008) Tanev & Bailetti (2008) Liu & Wang (2008) Fleischer (2008) Trim & Lee (2008) Calof & Wright (2008) Dishman & Calof (2008) Michaeli & Simon (2008) Tanev & Bailetti (2008)	Opait et al (2016)	Grower et al (2018) Merendino et al (2018) Wang et al (2018)
AC	Laidner & Elam (1993;1995) Laidner et al (1999)			Vlaene & Van den Bunder(2011) Sharma et al (2014) Shoilo & Galliers (2015) Aker et al (2016)	Córtie-Real et al (2017) Wamba et al (2017) Ghasemaghali & Calic (2020) Bordeleau et al (2020) Constantiou et al (2019) Urbinati et al (2019) Mikalef et al (2019) Lin & Kunnathur (2019)
AT	Elofson & Kossajnski (1991) McCrohan (1998) Vedder et al (1999)	Kohavi et al (2002) Srivastava & Cooley (2003) Wei & Lee (2004) Chung et al 2005 Sheng et al (2005)	Chau et al (2007) Li et al (2008) Cheng et al (2009) Lin et al (2009)	Chaudhuri et al (2011) Xu et al (2011) Cheung & Li (2012) Chen et al (2012) Lau et al (2012)	Moro et al (2015) Chen et al (2015) Gupta & George (2016) Popović et al (2018)
MI	Zajac & Bazerman (1991) Maltz & Kohli (1996) Slater & Narver (2000)	Le Bon & Merunka (2006)	Christen et al (2009)	Zheng et al (2012) Hughes et al (2013) Ahearne et al (2013)	Mariadoss et al (2014) Kumar et al (2020)
DS	Jones & Mcleod (1986) Watson et al (1991) Belcher & Watson (1993) Volonino et al (1995) Pawar & Sharda (1997)	Singh et al (2002) Heinrichs & Lim (2003) March & Hevner (2007)		Elbashir et al (2011) Ramakrishnan et al (2012) Popovic et al (2012)	Holzapfel et al (2014) Kowalczyk & Buxmann (2015) Averssa et al (2018) Audreyeva & Hudson (2016)
	<i>Formation of the six clusters</i>		<i>Differentiation and overlap between the six clusters</i>		

Figure 2. Evolution of BI literature

FUTURE RESEARCH AGENDA

Although theoretical pluralism has enriched the BI domain, the business and informatics communities failed to reach a common scientific epistemology and engulfed the research into two diverged views of BI. Research stemming from the informatics community has been concerned with developing the ultimate BI software capable of generating reliable intelligence. This yielded technologies responsible for converting mostly unstructured data into a homogenous piece of knowledge. Conversely, business scholars revealed a particular interest in the structure of any firm's industry as a prerequisite to formulating viable strategies. Their outside-in perspective to make sense of the environment uncertainty generated a nearsighted batch of works where the external environment and operational effectiveness are visible, whereas the distinctive competence and capabilities of organizational actors appear blurry. As a result, one can best capture the BI literature under the tree metaphor with its roots in the business community, and its leaves in the informatics research. Similar to its pluralistic theoretical landscape, BI research draws from overlapping views of BI as illustrated in Table 1. We, therefore, pinpoint to the need of conceptual unification should scholars bridge their fragmented community. In this vein, we suggest a comprehensive umbrella term where BI is synonymous with a computerized system that runs a gamut of technologies to perform an iterative and recursive process. This latter comprises four phases: 1) the collection of outer and inner data, 2) the transformation of data to actionable intelligence, 3) the impartment of knowledge to business users, and 4) the monitoring of organizational exploitation and absorption of knowledge. In what follows we offer research suggestions that shall shed light on the research gaps of each cluster as Table 1 illustrates.

Clusters	Stand on BI	Main theories & heuristics	Methodological Shortcomings	Research Gaps
ES	The collection of external data.	SCP paradigm; Organization Behavior theory.	Lack of surveys of western executives Lack of cross-case studies Lack of cross-functional studies Lack of cross-country studies Lack of conceptual studies Lack of literature reviews Lack of ethnographies and explanatory studies Lack of mixed methods	The impact of institutional pressure on scanning The role of cross-functional scanning behavior The relationship between scanning and organizational culture The relationship between institutional isomorphism and ES
CI	A product of actionable intelligence A 4-phase process (planning, collection, analysis, communication)	Porter's Five forces; SWOT analysis; Market research; CRM.	Lack of surveys of western executives Lack of cross-case studies Lack of cross-functional studies Lack of conceptual studies Lack of ethnographies and explanatory studies Lack of mix methods	The revision of The CI cycle to account for intelligence exploitation The relationship between The CI cycle and absorptive capacity The relationship between competitive intelligence and organizational structure and strategic decision making The issue of scope and focus in The CI cycle The integration between CI and MI
AT	A set of technologies that transforms data to actionable intelligence.	Functional linguistic theory; Sentiment analysis; Analytic hierarchy process.	Lack of qualitative studies Lack of ethnographies Lack of action research Lack of applications	The relationship between BI and strategy work. The role of BI applications in enabling strategic agility The impact of BI technologies on behavior change of organizations and business users The degree of dependence between competitive advantage and BI as a resource and investment
DS	An interface where executives can retrieve data and perform queries. A system that prepares data for the business user.	Contingency theory; Systems theory; Chandler's "structure follows strategy"; Simon's model of decision making; Organizational ecology; Transaction cost economics.	Lack of consolidative literature reviews Lack of cross-disciplinary conceptual studies Lack of ethnographies and sociological approaches Lack of longitudinal case studies	The relationship between DSS, EIS, and social exchanges in strategy work. The relationship between routinization of strategy processes and DSS/EIS The role of organizations' readiness for DSS/EIS and the success of their adoption in strategy work The relationship between organizational infrastructure, inertia and the implementation of DSS/EIS in strategy work
MI	The gathering of customers and competitors' data.	Nielsen & Dirichlet market measures; Social Exchange theory; Cognitive selling paradigm; Expectancy theory.	Lack of qualitative case studies Lack of cross-functional and cross-country studies Lack of conceptual studies Lack of ethnographies	The influence of individual constructs like credibility and job involvement of boundary spanners' on their behavior toward intelligence collection and dissemination. Determinants of the quality of boundary spanners' intelligence activities. The relationship between intelligence implementation, credibility, and persuasiveness of the sender The relationship between intelligence adoption and structure holes and social network in the case of formal and informal intelligence unit.
AC	A facilitator of participatory process of knowledge creation.	Practice theory; Organizational learning theory; Knowledge based view	Lack of quantitative studies Lack of literature reviews Lack of ethnographies Lack of explanatory studies Lack of cross-functional studies Lack of mix-methods	The impact of the intelligence activity on organizational knowing The impact of intelligence practices on existing organizational practices The influence of the intelligence activity on sensemaking The impact of the intelligence activity on strategy process

Table 1. Research agenda for the clusters of the BI research.

The Environmental Scanning (ES) cluster

Most research stemming from this cluster investigated the relationship between strategic uncertainty and the scanning behavior of executives in western countries. However, we still need more comparative studies to verify whether the positive correlation found in western environments are also valid in non-western environments, transitional economies, and highly institutionalized contexts (Ebrahimi, 2000; Elenkov, 1997). For this, studies shall alter to a more dynamic view of the environment, wherein we need a framework capable of capturing today's business environment. Further improvement of environmental scanning theory can also emanate from grounded theory to decompose the scanning behavior construct, and decipher its relationship with perceived strategic uncertainty in dynamic environments through processual studies in order to capture any refinement or degradation in the scanning behavior of executives (Boyd & Fulk, 1996; May et al., 2000). By so doing, research could explore the potential existence of nonlinear correlations between scanning behavior, managerial cognition, and strategic decision-making (Qiu, 2008). The ES cluster should adopt an inside-out perspective to verify the results indicating an influence of organizational strategy, structure, and processes on the scanning behavior of executives (Weick, 1979; Hambrick, 1982; Hrebiniak & Joyce, 1985; Hodgkinson & Johnson, 1994; May et al., 2000). Further research should also be directed toward the outcomes of environmental scanning in benign and dynamic environments and verify its influence on strategy work, strategic orientation, competitive advantage (Ebrahimi, 2000; May et al., 2000), and strategic decision making in both western and non-western contexts (May et al., 2000).

The Competitive Intelligence (CI) cluster

Since its inception, the competitive intelligence (CI) research focused on the external environment and turned out descriptive and exploratory publications of CI practices in western environments (Fleisher et al., 2008; Wright & Calof, 2006; Wright et al., 2009). This logic failed to operationalize the CI cycle and produce measures to evaluate its performance (Wright & Calof, 2006). Therefore, research should tap into the resource-based view to position the CI function within the organization, conceptualizes its formalization, and integrate its cycle with organizations' strategic processes, and management systems (Dishman & Calof, 2008; Fleisher et al., 2008). Further studies should also investigate the scope of the CI function, frame the needed practices, and decompose its activities into constructs that both managers and scholars could identify, measure, and evaluate (Wright & Calof, 2006). Research should attenuate its prescriptive pattern, and conduct more case studies that illustrate the actual practice of CI in various contexts, and explain the strengths and shortcomings of informal and formal CI units concerning the CI best practice model and their value to strategy work and firms' performance (Wright & Calof, 2006; Wright et al., 2009). Finally, further work investigating the competence of CI agents and the comprehensiveness of the CI process (Planning, collection, analysis, and communication) is undoubtedly instructive. For instance, we know little about the role of CI officers in propagating the intelligence culture inside organizations, not to mention the need to explore how the CI cycle permeates and nurtures this culture (Trim & Lee, 2008). Scholars should turn their attention to the breadth of the CI cycle that fails to follow the disseminated intelligence and account for its exploitation and absorption throughout the organization (Trim & Lee, 2008).

The Market Intelligence (MI) cluster

Extant research in this cluster adopted a quantitative approach and focused heavily on salespersons' behavior toward the participation in collecting and communicating market intelligence (Le Bon & Merunka, 2006; Ahearne et al., 2013). Research examining the quality of salespersons and other boundary spanners is, nonetheless, absent (Le Bon & Merunka, 2006). Likewise, research examining managers' perception of boundary spanners' intelligence efforts is lacking (Le Bon & Merunka, 2006). With that said, scholars can turn to social judgement theory to explore the issue of legitimacy and persuasiveness between the intelligence sender and receiver, and explore organizational citizenship behaviors (OCBs) to investigate the role of job involvement, recognition, and motivation vis-a-vis the intelligence efforts of boundary spanners (Le Bon & Merunka, 2006). Additionally, future work can look at the antecedents of intelligence quality stemming from boundary spanners and the impact of their social capital on the collection of high-quality intelligence (Le Bon & Merunka, 2006; Hughes et al., 2013). More research examining the boundary spanners' intelligence collection networks (informal vs formal) and its relationship with firm performance is needed (Ahearne, Lam, Hayati, & Kraus, 2013). Besides, future research should account for the difference between tacit and articulated knowledge and address how each type supplements strategy work, and feeds the intelligence culture and organizational learning (Ahearne et al., 2013). Lastly, further research needs to view the intelligence activity as a resource and capability for achieving competitive advantage (Kohli & Jaworski, 1990; Narver & Slater, 1990; Day, 1994; Hughes et al., 2013) in order to investigate the intelligence collection and dissemination in relation to strategic decision-making, strategy formulation and implementation (Hughes et al., 2013).

The Decision Support (DS) cluster

This literature strives to explore the impact of decision support systems (DSS) on organizational learning and executive decision-making (Elbashir et al., 2011; Kowalczyk & Buxmann, 2015). The research herein commenced with the concept of Decision Support Systems (DSS), transitioned to Executive Information Systems (EIS), and shifted to Business Intelligence (BI). Unfortunately, middle and front-line managers and various business users seem discarded by this cluster's line of thinking and therefore call for scholars' attention. Similarly, further research should adopt both macro and micro perspectives following structuration theory and social exchange theory in tackling the relationship between the social structure of organizations and agents' social exchanges and BI. This suggestion finds validity in research suggesting that successful technology innovation and management systems implementation are bottom up rather than top down and result from developing a suitable organizational capability (Elbashir et al., 2011). Similarly, understanding the impact of ambidexterity and inertia on BI and their derived tensions influencing BI success also represent interesting research directions. This avenue finds motivation in previous results that place institutional isomorphism and inertia as an independent variable for BI implementation (Ramakrishnan et al., 2012; Audzeyeva & Hudson, 2015), and suggest a positive correlation between high degrees of ambidexterity and astute decision making (Kowalczyk & Buxmann, 2015). Finally, the linkage between organizational structure and BI still arises as an underexplored area and requires researchers to investigate which structure represents an environment ripe for effective intelligence use: organic or mechanistic structure. However, the causality chain of this linkage is still unclear and deserves further exploration similar to the causation link between strategic orientation (cost leaderships/differentiator) and BI.

The Analytics Technologies (AT) cluster

In spite of its dominance over the BI scholarly community, this research stream discards any cross-disciplinary agenda with the other clusters, let alone the positioning of BI in strategy work. Research in this cluster is ad-hoc and highly technical centered on BI as a computerized system rather than its outcomes or the needs of business users (Brichni et al., 2017; Chau et al., 2007; Chen et al., 2002; Chung et al., 2005; Lau et al., 2012; Moro, Cortez, & Rita, 2015; Opait et al., 2016). Scholars, therefore, should direct their attention to the role BI could play in strategic decision-making and investigate the residual value of BI for organizational learning across various industries. Similarly, this new research could draw from the resource dependence theory to explore the impact of BI technologies as a resource on the change of behavior across the organization and business users. In this vein, longitudinal studies enable scholars to tap into the behavior changes prior and after investing in BI technologies (Thomas et al., 1991) and track managers' intelligence use as they assume high-level positions (Jones & McLeod, 1986). Moreover, today's dynamic environment encourages scholars to examine the relationship between BI and strategic agility of organizations and executives' decision-making. In this regard, scholars can import the notion of dynamic capabilities to understand better the ability of BI to provide decision makers with actionable knowledge upon which they can act swiftly in dealing with the versatility of environment.

The Analytics Capabilities (AC) cluster

This nascent research stream draws from practice theory, and actor network theory, and aspire to emulate the Strategy as Practice (SAP) research in analyzing the micro-role of BI in organizational learning processes and dynamic capabilities (Côte-Real et al., 2017; Mikalef et al., 2019) and

within the microprocesses of organization strategy work by top management teams and middle managers (Peppard et al., 2014; Shollo & Galliers, 2015). While this research investigates the influence of BI on the practices conducive to knowing (Shollo & Galliers, 2015), it seems about time to highlight its need to explore the issue of socio-materiality of BI and examine how it entangles with social practices in strategy work. Following the SAP tradition that pictures strategy work as dependent upon an ongoing sense-making activity between managers and subordinates to decipher meaning out of paradoxical problem definitions or solutions, the Analytics Capabilities (AC) cluster can tap into the role of BI in shaping the interactions and interpretations of reality. This tradition of interactionism draws from sociology and behooves turning attention to all participants in the social activity of strategy work (Blumer, 2012) where sensemaking is subject to multiple interest groups that might encounter rivalry, opposition, or confrontational framing contests, in which contestants establish control over reality interpretation (Entman, 2003). In this vein, AC scholars should address the role of BI in relation to these confrontations and the manner whereby it influences frames contestation and sense making.

CONCLUSION

The BI research is far from exhaust. Its growth into a fragmented research has witnessed two periods of ferment following two pendulum swings that advanced the research toward theoretical pluralism. While this state of affairs contributed to the enrichment of our knowledge of BI, it plunged the field into overlapping research endeavors that hampers the field's advancement toward maturity. Therefore, our paper attempts to build consensus across the BI scientific landscape and pinpoint to where research gaps still await attention. We highlight the theoretical underpinnings of BI research and underscore the shared commonality among BI scholars in spite of their different

research clusters. This article, therefore, contributes to the extant literature by 1) decomposing the BI scientific landscape to six research streams, 2) diagnosing the theoretical underpinnings of each research cluster, 3) mapping the evolution of BI scholarly community, and 4) suggesting a new agenda for future research.

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Appendix 1. Search process of articles

TITLE-ABS-KEY ("business intelligence" OR "business intelligence model*" OR "competitive intelligence" OR "market intelligence" OR "executive information system*" OR "decision support system*" OR "business analytic*" OR "data mining" OR "data*warehous*" OR "online*analytic*processing" OR "extract*transform*load" OR "environment*scanning" OR "customer intelligence" OR "environment*analy*i*" OR "financ*intelligence" OR "structured query language" OR "relational database management system*" OR "data mart" OR "data discovery" OR "dashboard" OR "process mining" OR "complex event processing" OR "Prescriptive analytics" OR "Predictive analytic*" OR "big data" OR "big data analytic*")

