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Recovering the divide: A review of the big data analytics—strategy relationship

Yassine Talaoui [a,*], Marko Kohtamäki [b], Mikko Ranta [c], Sotirios Paroutis [d]

[a] *University of Vaasa, School of Management, PO Box 700, FI-65101, Vaasa, Finland*
[b] *University of Vaasa, School of Management, University of South-Eastern Norway, USN Business School, Luleå University of Technology, Entrepreneurship and Innovation, PO Box 700, FI-65101, Vaasa, Finland*
[c] *University of Vaasa, School of Accounting and Finance, PO Box 700, FI-65101, Vaasa, Finland*
[d] *Warwick Business School, The University of Warwick, Coventry, CV4 7AL, UK*

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ABSTRACT

Research on big data analytics has been burgeoning in recent decades, yet its relationship with strategy continues to be overlooked. This paper reviews how big data analytics and strategy are portrayed across 228 articles, identifying two dominant discourses: an input-output discourse that views big data analytics as a computational capability supplementing prospective strategy formulation and an entanglement discourse that theorizes big data analytics as a socially constructed agent that (re)shapes the emergent character of strategy formation. We deconstruct the inherent dichotomies of the input-output/entanglement divide and reveal how both discourses adopt disjointed positions vis-à-vis relational causality and agency. We elaborate a semiotic view of big data analytics and strategy that transcends this standoff and provides a novel theoretical account for conjoined relationality between big data analytics and strategy.

1. Introduction

New digital applications increasingly conduct the policy, actions, and affairs of all aspects of our lives (Bailey et al., 2019). The byproduct of this digital revolution is a deluge of big data that carries a lucrative opportunity for Big Tech—Apple, Facebook, Microsoft, Google, and Amazon—to develop novel analytics to allow companies from all sectors to harness and leverage these vast troves of free-flowing data. A clear illustration of this interest is reflected in Big Tech, Big Pharma, policymakers, and health institutions leaning together toward big data analytics to respond to the COVID-19 global pandemic and anticipate the next unforeseen 'black swan' event (Sheng et al., 2021; Ienca and Vayena, 2020; Wang et al., 2016). Another example of its centrality can be found in many studies showing how big data analytics has become indivisible from strategic decision-making (e.g., Fitzgerald et al., 2014; Hanelt et al., 2020; Rogers, 2016), or in research going as far as enthroning it as sustenance for addressing emerging digital trends and new rules of value creation and capture (e.g., Constantinides et al., 2018; George et al., 2016; Hautz et al., 2017; Jacobides et al., 2018).

While scholars have lauded big data analytics as a dynamic capability that could innovate business models (e.g., Davenport and Barth, 2012; Davis, 2014; Holsapple et al., 2014) and enable data-driven strategic planning (e.g., Gupta et al., 2017; Müller and Jensen,

* Corresponding author.
E-mail addresses: yassine.talaoui@uva.fi (Y. Talaoui), marko.kohtamaki@uva.fi (M. Kohtamäki), mikko.ranta@uva.fi (M. Ranta), Sotirios.Paroutis@wbs.ac.uk (S. Paroutis).

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2017), there is a caveat that concerns the intelligent and emergent character of big data analytics, which carries a set of circumstances that make it possible to reshape strategy practices and processes (Volberda et al., 2021), challenge practitioners and academics dealing with theories and empirics of cognition and action (Van Knippenberg, Dahlander, Haas and George, 2015), and defy traditional conceptualizations of its status and place in strategy work and research (Bailey et al., 2022; von Krogh, 2018). Despite this proviso, there is still a paucity of work investigating the status of big data analytics in strategy work and the ways we construct the big data analytics—strategy relationship in our written scholarly work and how our writing reflects, produces and shapes our thinking about such a relationship (Bailey et al., 2019; Orlikowski and Scott, 2008; Volberda et al., 2018; Zammuto et al., 2007).

Against this backdrop, this paper pays particular attention to the 'how' of this relationship and does so by dismantling the conditions and assumptions that inform the work of scholars toward the body of knowledge that we have today on big data analytics and strategy (Orlikowski and Baroud, 1991). We do not exclude any scientific field to allow for a comprehensive and multidisciplinary bundle of 228 empirical and conceptual articles on big data analytics and strategy spanning 26 years (1995–2021) of research published in the 2021 Academic Journal Guide (AJG).

Our review deploys an exploratory transformative mixed methods design (Aranda et al., 2021; Brookes and McEnery, 2019; Creswell, 2009; Creswell et al., 2003; Wodak and Meyer, 2016) because it carries a deconstructive purpose where it aims at fleshing out the workings of language and meaning to expose discursive components that form certain ideologies about the big data analytics—strategy couplet (Aranda et al., 2021).

For quantitative reliability, our mixed-methods design relies on Latent Dirichlet Allocation (LDA) to reduce the chunk of text to the two discourses holding disjointed views on the relationality of big data analytics and strategy. First, an input-output discourse separates big data analytics from strategy actors and strategy processes and practices, and then juggles causality between big data analytics and the sphere of strategy work (Faraj and Pachidi, 2021; Feenberg, 1999; Kelly, 2010; Winner, 1977). The second is an entanglement discourse that joins big data analytics to the social context of strategizing to explore the affordances of big data analytics and how strategists can leverage them to convert workflow processes to an automatic operation (Braverman, 1974; Edwards, 1979; Noble, 1977; Zuboff, 1988). For qualitative reflexivity, we avail ourselves of deconstructive discourse analysis to dismantle both discourses and expose their respective dichotomies, which foster tensions vis-à-vis relational agency and causality.

Laying bare these points of rupture allows us to recover the discursive divide that disjoints the relationality of big data analytics and strategy. By so doing, this article contributes to the materiality turn in strategy as practice by focusing on the big data analytics—strategy relationship as a genre that significantly structures activities of managers and other organizational members (e.g., Lê and Spee, 2015; Levina and Orlikowski, 2009; Orlikowski and Yates, 1994; Peppard et al., 2014; Vaara and Whittington, 2012; Whittington, 2014), and attending to new ways big data analytics enables us to explore organizational phenomena such as strategizing (Bailey et al., 2019). We organize the rest of this article as follows. First, we summarize the theoretical understandings of the big data analytics—strategy relationship. Second, we introduce our explanatory transformative mixed methods design followed by a presentation of the input-output and entanglement discourses that motivate the treatment of the big data analytics—strategy relationship. Third, we deconstruct the discursive divide to reveal contradictions and oppositions alimenting a disjointed relational causality and agency between big data analytics and strategy and close with a semiotic view toward their conjoined relationality.

2. Conceptual background

2.1. Understandings of the big data analytics—strategy relationship

Previous reviews on big data analytics bifurcate into two views (see Appendix 1): one that trusts it to innovate strategy making processes and upscale business models (e.g., Davenport and Barth, 2012; Davis, 2014; Holsapple et al., 2014; Kiron et al., 2014; McAfee and Brynjolfsson, 2012; Mikalef, van de Wetering and Krogstie, 2021), and another that emphasizes its analytical technologies toward enabling informed strategic planning and decision-making (e.g., Gupta et al., 2017; Müller and Jensen, 2017; Roden et al., 2017; Sivarajah et al., 2017; Trieu, 2017; Wang et al., 2016). Such a treatment overlooks the status and nature of big data analytics and the ways it intrudes and shifts existing routines and practices of strategy work (e.g., Abbasi et al., 2016; Bačić and Fadlalla, 2016; Kwon et al., 2014; Loebbecke and Picot, 2015; Mora et al., 2005; Moro et al., 2015) despite evidence suggesting that it is the interplay between big data analytics and the organizational social milieu that triggers social and technological processes to meet intended strategic goals (Baptista, 2009; Baptista et al., 2021; Beynon-Davies, 2011; Beynon-Davies et al., 2009; Constantiou and Kallinikos, 2014). For instance, if the intended affordances of big data analytics diverge from the expectations of strategy actors, conflicts erupt, then trigger the change of routines (Berente and Yoo, 2012; Hultin & Mähring, 2014) and eventually accord a different meaning and status to big data analytics.

New technologies such as big data analytics are intelligent insofar as they carry a disruption risk that extends beyond automating and feeding existing processes with data and arise because of their ability to be autonomous, learn, and operate in ways that increasingly seem intentional and able to replicate, if not exceed, human cognition (Bailey et al., 2019). As such, big data analytics challenges its conceptualization frameworks and prompts scholars to take its status seriously and rethink taken-for-granted assumptions about its role in the doings of strategy, not to mention its relationship with human and social dynamics (von Krogh, 2018).

As a consequence, scholars have called for new perspectives, such as the sociomaterial lens (Leonardi and Barley, 2010; Orlikowski and Scott, 2014), that involve theorizing beyond the functionalities and usage of big data analytics that permeate available research. Despite these efforts to explore and devise linkages and synergies between big data analytics and strategy (Benbya et al., 2019), research still lacks a clear understanding of the nitty-gritty big data analytics mechanisms that give rise to strategy at a micro level (Baptista et al., 2021) or of the role of human actors in aligning big data analytics with strategy imperatives (Karpovsky and Galliers, 2015). To date, research still has not reconceptualized the role of big data analytics in the essential microprocesses of strategizing to enact strategic objectives (Arvidsson and Holmstrom, 2018; Arvidsson et al., 2014; Peppard et al., 2014; Whittington, 2014) and its influence on the day-to-day activities that constitute the mode of formation of the doings of strategizing and, by extension, realized strategy (Kouamé and Langley, 2018).

Against this backdrop, it is worth problematizing big data analytics-based practices and whether their reconfiguring brings any value or significance to strategy work. Addressing this avenue requires diverging from traditional views that problematize big data analytics as an issue of execution or a local feedback issue toward reconceptualizing big data analytics—both its role in and significance to strategizing—in a way that transcends the immediate consequences of technological change or digitization. In this vein, we undertake a review of the literature on the big data analytics—strategy relationship to uncover the ways both concepts are portrayed and what implications we can derive from such portrayals. Our review, following Leidner's (2018) typology, falls somewhere between an assessing review and a specific theorizing review. This positioning is due, on the one hand, to our inclination to provide a synthesis of the discourses identified within the literature on big data analytics and strategy, and to our focus on one gap in the literature, the big data analytics—strategy couplet, for which we seek to provide theoretical filling.

Our notion of big data analytics encompasses all the progress of big data analytics in the past two decades and covers all its associated terms. We follow Simsek et al. (2019)'s recommendation of adopting big data analytics as a comprehensive label that covers data collection, organizing, storage, retrieval, analysis and dissemination involving all kinds of data types and volumes, and ascribe to Lavalle et al. (2011), Chen et al. (2012), McAfee and Brynjolfsson (2012)'s views of big data as an extension of digitization, business intelligence and analytics. Our review starts from 1995 to account for what Chen et al. (2012) refer to as the 1.0 period, which witnessed the popularization of the analytical techniques of big data analytics.

3. A mixed methods approach: integrating deconstructive discourse analysis and Latent Dirichlet Allocation

Integrating quantitative and qualitative methodologies — such as human-based deconstructive discourse analysis and machine-based Latent Dirichlet Allocation (LDA) — carries an epistemological challenge. LDA follows an inductive and algorithmic process of topic and discourse generation that marginalizes human input, which can seem pointless and uninspiring for interpretivist scholars; the emergent character of deconstructive discourse analysis involves human input and abductive reasoning in reading texts and subjectively interpreting its meanings, which can be questionable for positivist data scientists used to estimation-controlled methods (Aranda et al., 2021).

However, it is the subjective nature of interpretative work that can integrate the two diverging paradigms (Gioia and Pitre, 1990) because although LDA follows an automated estimation process, human interpretation occurs at different stages of it (Hannigan et al., 2019), which weaves together human agency with that of the LDA algorithm (Aranda et al., 2021). Akin to deconstructive discourse analysis, in LDA neither the human nor the algorithm conducts the analysis separately, but it is their mutually constitutive series of selections across ranges of possibilities that shape the results of topic and discourse estimation (Wodak and Meyer, 2016). This process of mutual constitution creates a dialogue between the human and the technique and circumvents their epistemological divergence (Hassard, 1988; Lewis and Grimes, 1999; Scherer, 1998), which lays down the foundation for engaging with their differences by

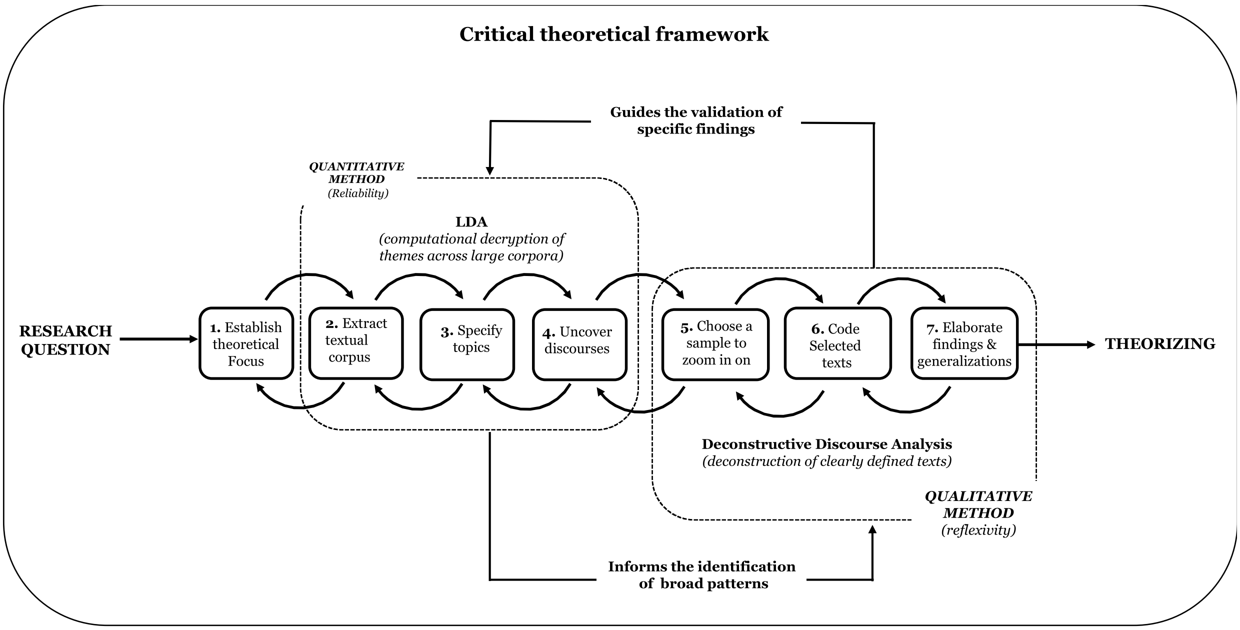

Fig. 1. Transformative exploratory mixed methods design (adapted from Aranda et al., 2021).

emphasizing the notion of complementarity between the two methods (Creswell, 2009; Creswell et al., 2003; Deetz, 1996). This complementarity is what our mixed methods design puts forward in a sequential and iterative process where LDA and deconstructive discourse analysis nurture a mutual relation (Creswell et al., 2003) in which interpretations guide LDA quantitatively derived topic estimates that inform deconstructive discourse analysis (Aranda et al., 2021).

Fig. 1 illustrates how the textual corpus of 228 articles was examined to uncover 2 discourses based on "the automated identification of relations" among 34 different topics (Aranda et al., 2021, p. 202). A detailed account of the systematic literature review process we followed to retrieve the 228-article sample appears in Appendix 2. Each step of our mixed methods design is reported in Appendix 3 to showcase how LDA automatically generated the 34 topics and their aggregate 2 discourses via topic linkages. Appendices 4 and 5 present the thematic meaning of both discourses. Fig. 2 portrays, on the left, the input-output discourse about big data analytics that mediates the descriptions of strategy context, and on the right, the entanglement discourse about the social consequences of big data analytics that mediates a reshaping of strategizing activities. Finally, Appendix 6 presents the coding strategies we followed to deconstruct both discourses into their dichotomies, which foster disjointed relational causality and agency between big data analytics and strategy.

4. Analysis and discussion

4.1. The input-output/entanglement divide

4.1.1. The input-output discourse

This discourse mirrors studies viewing big data analytics as a computational capability to grasp the strategy context and therefore draws from the prescriptive tradition of strategy research, which assumes that structured, quantitative, and intentionally collected data feed into strategy processes (Pfeffer and Sutton, 2006). The prescriptive undertone of this discourse represents the content and planning schools of strategy that conceive of strategy as planned and deliberate activity toward reaching outcomes in a Schumpeterian market. The dynamism and uncertainty inherent to that market force companies to collect and monitor intelligence on all the industry players to foresee any disequilibrium that would jeopardize their market positioning (Constantiou and Kallinikos, 2014; Priem et al., 2013).

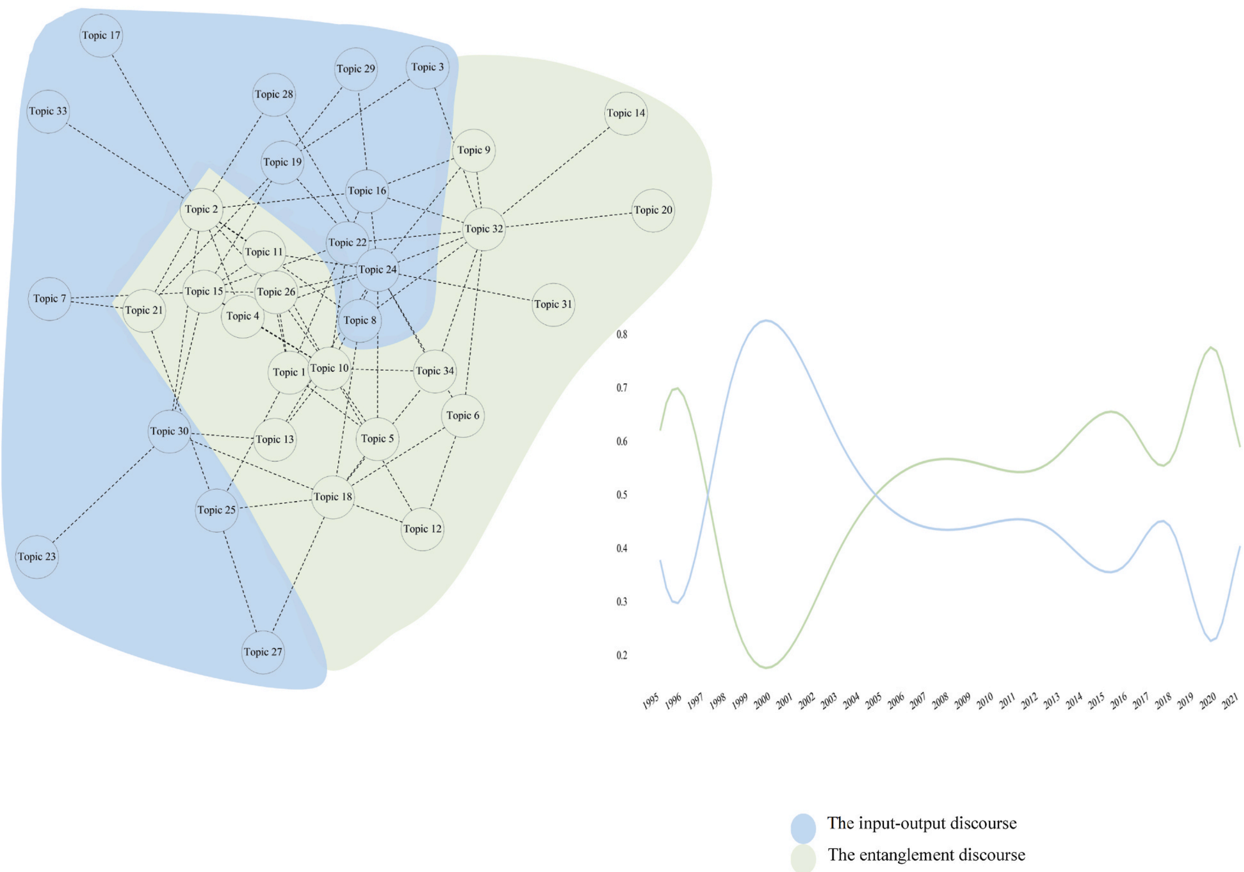

Fig. 2. Topic relations and associated discourses.

The excessive focus on environmental contingencies and the influence of industrial organization economics (Bain, 1956; Mason, 1939; Porter, 1979) on these schools of strategy produce an outright focus on deductive mathematical and statistical algorithms and technologies of big data. These computational technologies follow models abstracted from the structure-conduct-performance-paradigm (S–C–P) (Bain, 1956, 1968; Mason, 1939), which assumes homogeneity among firms within the same industry (Hatten and Schendel, 1977). Therefore, the input-output discourse follows an outside-in sequence of industry analysis to determine the position of a firm vis-à-vis its rivals, to investigate market structure (Hoskisson et al., 1999), and to model the influence of both strategy and structure on the firm's performance (Hitt et al., 2021).

Conversely, internal proprietary research, rooted in organizational economics with its transaction costs emphasis (Williamson, 1975, 1985) and agency theory (Coase, 1937), creates a need for intelligence analytics capable of tracing and illustrating the inner structural logic and functioning of the firm and of defining key variables necessary to measure, evaluate, and understand the influence of the firm's internal mechanisms on strategy and performance (Godfrey and Hill, 1995).

This shift to the firm results in a need to upgrade big data analytics to a computational capability to capture the organizational resources of the firm, anticipate reactions of competitors, as triggered by actions initiated by the focal firm (Bettis and Hitt, 1995), and to examine the development and accumulation of knowledge within a firm and its competition. As such, big data analytics prioritizes necessary input to strategy formulation through a systematic environmental analysis consorted with an appraisal of the firm's internal distinctive competence (Selznick, 1957).

Unfortunately, swiftly constructing decisions relative to environmental changes is easier said than done, especially due to the combination of rigid inertial forces and the inability of managers to assess disruptions and decipher meaning from what might seem merely noise (Kaplan, 2008; Knight, 1965). Such a commotion shakes the management of organizations a great deal and poses a stiff challenge for strategy work, which behooves managers to match their interpretation of what is going on with making sound strategic choices (Bower, 1970). Alternatively, the discourse assumes that turbulence in the environment cannot be pictured as a set of easily identifiable indications and pinpoints managerial cognition as a major player to muddle through ambiguities (Walsh, 1995). The rationale is that managers' frames of interpretation, which serve to interpret and translate signals into decisions, exert a major influence on strategy work during upheavals (Barr, 1998; Tripsas and Gavetti., 2000).

4.1.2. *The entanglement discourse*

The second discourse veers off from the outside-in and inside-out views of the prescriptive schools of strategy to focus on the agential role of strategy actors and processes by which these actors deal with big data analytics (Constantiou and Kallinikos, 2014), along with practices that entangle them. Contrary to the input-output discourse, big data analytics is portrayed here as an agent that deals with unstructured data that are not collected intentionally but in a haphazard and heterogeneous modus operandi (Anderson, 2008). As such, big data analytics befits a different character of strategy that is enmeshed in the doings and sayings of people (Jarzabkowski, 2005; Johnson et al., 2007). In this vein, the entanglement discourse adopts a sociological lens to explore strategy anew to catch interactions of actors as they incorporate big data analytics into strategic activities and investigate outcomes pegged to its usage in disseminating insights to actors engaged in the social practice of strategy work (Bakke and Bean, 2006; Garreau et al., 2015; Jarzabkowski and Kaplan, 2015; Whittington, 2007).

As a result, this discourse finds in the strategy-as-practice (SAP) scholarship social grounds for the doings of strategy that help the proponents of this discourse theorize the big data analytics—strategy couplet as part of a social order, not as a structure or resources (Constantiou and Kallinikos, 2014). This implies the performativity of strategy doings that entwine the realities of both the strategist and big data analytics and afford different manifestations of strategizing activities (Cabantous et al., 2018). Therefore, the doings of strategy shift the traditional focus of big data analytics as a mediator of strategy context (first discourse) from epistemological inquiries (Wright, 2017) to ontological questions about the status and agency of big data analytics and strategists who shape the realities of strategy doings (Garud et al., 2018). These realities do not predate the practice of strategy but are continuously "constituted, deconstituted, and reconstituted" in situ, and therefore cannot be fathomed as a representation of a preexisting reality, but a reality that comes out from the performativity of strategy doings that could be captured by adopting a different stance (Cabantous et al., 2018, p. 412).

As a result, the materiality of big data analytics is paramount within the second discourse, which explores its mediating role in changing the social dynamics of strategizing activities because the affordances of big data analytics provide strategy workers with the ability to strategize in ways that they could not have known of previously (Leonardi and Barley, 2008). Within this discourse the big data analytics—strategy relationship is central to our normative understanding of who is a strategist and what strategizing is (Balogun et al., 2014; Callon and Law, 1997; Jarzabkowski et al., 2013). This is clear in the emphasis of this discourse on the entanglement of strategy actors and big data analytics in strategizing activities to the degree that strategists arise through their embodied interactions with big data analytics that make such an identification possible.

In this context, the second discourse conceptualizes strategizing processes and meaning-making as a materially mediated stream of activities in which strategists accomplish tasks using big data analytics. Meanwhile, it focuses on the affordances of big data analytics as a sociomaterial agent that shapes the strategy work being performed and stimulates organizational members engaged in its doings. These studies show that big data analytics shapes strategizing activities by enabling or constraining practices of the agents involved in it and their meaning-making (Bakke and Bean, 2006; Garreau et al., 2015; Jarzabkowski and Kaplan, 2015).

4.2. Deconstructing the input-output/entanglement divide

4.2.1. The input-output discourse

The text carrying the input-output discourse interprets big data analytics as an imperative, whether in emergent or fully developed form. It thus enlists it to sustain an elusive competitive advantage but ignores how often it weaves into strategy doings (e.g., Boyton et al., 2015; Dahiya et al., 2021; Gaidelys and Dailydka, 2016; Gershon Richard A, 2000; Işik et al., 2013). For this purpose, the text emphasizes the necessity of integrating technological disruptions into logical, structural, and positivist models and strategy tools (e.g., the strategy map, the balanced scorecard, Porter's five forces, etc.) to accommodate its premise of big data analytics' inexorable occurrence in strategic planning. It hence attempts to create an input-output model for strategic planning, which isolates the analytical facet of strategizing from the social dynamics that enact the strategizing activities.

This input-output model treats big data analytics as a computational capability with a crucial role in forming organizational structure (Lawrence and Lorsch, 1967; Thompson and of, 1967; Woodward, 1965), determining how inputs turn into outputs (Perrow, 1984), and reporting workflows (Scott and Davis, 2007). The text holds that big data analytics must be preserved, upgraded, and improved to ensure the continuity of its value (Faraj and Pachidi, 2021). For instance, this input-output view posits that the big data analytics that organizations possess differentiates their structures, and therefore they must safeguard it against adverse effects of the environment (Faraj and Pachidi, 2021; Thompson and of, 1967; Woodward, 1965). Accepting the input-output view leads designers to promote big data analytics' information processing component, which shifts the focus toward carefully designing complex and logical architectures that shield its information processing capacity (Faraj and Pachidi, 2021). Second, rising uncertainty in the business environment shifts attention toward making processed information correspond in some essential respect to the needs of competitive dynamics (Galbraith, 1973; Nadler and Tushman, 1988).

To establish the input-output model of strategy work, the text deploys existing theoretical frameworks of the content school of strategy and pays particular attention to environmental uncertainty, not as an antecedent to strategic planning but as its core issue. In fact, the text takes up a 'mirror perspective' to presuppose that big data analytics in fact reflects a 'factual world' out there (Gephart, 1996; Rorty, 1979). By arguing for the need to move environmental uncertainty from the periphery to the center of theorizing, the text adopts an information-oriented view of strategy. That view entails big data analytics becoming a computational capability because it influences the organization's demand for and capacity to process information and allows organizational stakeholders to transfer factual intelligence across organizational layers (Burton et al., 2011; Faraj and Pachidi, 2021). The text therefore elicits a conservative view (Jameson, 1991, p. xviii) of present and future organizations as "postindustrial" (Shrivastava, 1995, p. 119) rather than "postmodernist" societies (Gephart, 1996, p. 207). It excludes social processes from acting upon big data analytics and invokes a one-directional argument that considers big data analytics the only decisive factor in the outcome of organizational structures (Baldwin, 2019) and the sociocultural order (Heilbroner, 1967; Leonardi and Jackson, 2004; Marx and Smith, 1994).

In fact, the text depicts the success of big data analytics in capturing the strategy context as a fact that has been decided before those participating in strategizing activities hear about it, therefore leaving them with no choice but to adopt big data analytics in their practices as 'a fait accompli', as the text takes a firm confidence in the power of big data analytics to challenge the canons of our approaches to strategy (Constantiou and Kallinikos, 2014) and not only cause but transform the social practice of strategizing itself (e.g., Cooper et al., 2000; Davenport, 2014). For instance, the text has a recurrent action of alluding to the 'inexorable' occurrence or advancement of big data analytics in strategic planning, processes, strategy workshops, and individual- or group-level decision-making (e.g., Rohrbeck, 2012; Tavana, 2002; Vilkkumaa et al., 2018). Similarly, the ability of big data analytics to intrude into strategizing practices and improve their flexibility, speed, and efficiency is reinforced through the text's supportive rhetoric (e.g., Davis et al., 2008; Ghasemaghaei and Calic, 2020; Liu et al., 2018).

The unavoidable agency of big data analytics in changing the nature of strategy work follows a top-down view of the firms that reduces the complex context of strategizing to a mere attending to the needs of executives while the other practitioners arise as a 'silent audience' (e.g., Constantiou et al., 2019; Merendino et al., 2018). This assumption is clear in affixing the word 'powerful' to the denomination of executives where 'powerful' insinuates the strong effect they have on their subordinates' feelings and thoughts (e.g., Cooper et al., 2000; Pryor et al., 2019). Another clue is apparent in the description of the process whereby executives influence their context as a 'black box' to suggest the intangible psychological factors that govern their behavior, namely their understanding of their firms' environments (e.g., Davenport et al., 2001; Gibbons and Prescott, 1996; Pryor et al., 2019; Voros, 2003).

Notwithstanding this deterministic view of big data analytics' influence on strategizing practices, a scrutiny of the text hints to a different meaning. In lieu of devising systems of production for ensuring big data analytics input and social conduct output, we detect that the text's instructions and directions in fact restrain the occurrence of big data analytics in strategizing practices by advancing two contradicting claims: one that promotes the relevant output of big data analytics (e.g., Dutta and Fourer, 2008; Hough and White, 2004) vs. another that highlights the intuitive judgments of strategists (e.g., Constantiou et al., 2019; McHardy, 1995). The premise of the first statement is that the intrusion of big data analytics in executives' decisions is a result of its relevant output. However, this position seems doctrinal when executives' intuitive judgments trump this same output.

Further evidence of these conflicting claims is rooted in the difficulty of modeling or anticipating the contextual acumen that makes up the intricacies of executives' intuitive judgments. Similarly, the instrumentality of big data analytics no longer seems to entail a radical shift of the doings of strategizing but seems to emerge from these same doings. The text recommends implementing big data analytics in a logic of discovery for emergent ways of doings that could be tested and integrated into the system (e.g., Ding and Shi, 2021; Garcia-Nunes & da Silva, 2019; Schoemaker et al., 2013).

The unavoidable occurrence also seems to require 'alignment' with the social context of strategizing because the 'maturity' of big data analytics is time and context dependent and therefore necessitates that big data analytics holds a 'strategic role'. The text notes that big data analytics should enjoy long-term involvement in strategy work and be aligned with organizational objectives for it to reach the required maturity level for contributing to value creation (e.g., Analoui and Karami, 2002; Dutta et al., 2007; Van Groenendaal, 2003). Therefore, for big data analytics to unleash its full agency to transform a firm into an agile organization (e.g., Gaidelys and Dailydka, 2016; Pellissier and Kruger, 2011; Tjader et al., 2014), it must be upgraded from a mere executive decision support 'resource' to a dynamic capability diffused across organizational layers (Ilmola and Kuusi, 2006; Klatt et al., 2011; Nyuur et al., 2015).

However, the text's unwavering obsession with executives' dominance emerges when it considers the plan for aligning big data analytics with strategizing practices. The text roots this position of 'fit' between the two elements of the big data analytics—strategy pair in the leadership of executives. This suggests that big data analytics depends on executives' vision and leadership and on a top-down approach that the top management devises, motivates and supervises (e.g., Boyton et al., 2015; March and Hevner, 2007). These accounts put the social dynamics of strategizing out of the realm of action and assign it a place of passivity, while granting big data analytics instrumentality and executive leadership a commanding position over action, although the text acknowledges the salience of big data analytics' diffusion across organizational layers for it to be conducive to business value (e.g., Cavallo et al., 2021; Gibbons and Prescott, 1996; Heinrichs and Lim, 2003).

A closer look at the guidelines for big data analytics' alignment across the social context reveals that data scientists arise as the new 'powerful' actors. The recommendation is that organizational barriers emanate because of big data analytics challenging the 'status quo power' rather than from social dynamics wherein other strategy participants may find discrepancies between their intended uses of big data analytics and their enactment of new unintended affordances, which might lead to their skepticism toward the enthusiasm spawned by executives over big data analytics. The text emphasizes the ability of big data analytics to reconfigure the relationship between the organization and its members insofar as it redefines lines of authority, influence, and organizational power (Davenport et al., 2001; Martinsons and Davison, 2007; Migliarese and Paolucci, 1995).

In these new power instances, the text puts forward data-savvy actors as being most suitable for the doings of strategy with big data analytics due to their expertise and knowledge of technological developments to drive business opportunities (e.g., Arnott et al., 2017; Davenport, 2014; Urbinati et al., 2019). However, the text records no comments on how such adroitness conceives of existing social structures and routines and whether the new data culture meets the acceptance and expectations of the different social stakeholders. In addition, the text is ambivalent about the 'non-data savvy' strategists who also participate in strategizing activities. The text frequently insinuates that they should ramp up their data 'adeptness' to maintain their roles and may even emerge as more influential than before (e.g., Grover et al., 2018; Merendino et al., 2018). Sporadically, the text alludes to the human strategist as someone who will be supplanted when the automation of business processes reaches its full potential and radically alters strategy processes and activities and the way business is conducted (Lau et al., 2012; Orwig et al., 1997; Thorleuchter & Van den Poel, 2015; Thorleuchter et al., 2014).

4.2.2. The entanglement discourse

The text adopts a posthumanist treatment of big data analytics that grants it the status of a protean agent and reinstates its role in producing strategizing practices. For this purpose, the text imposes uniformity between strategy actors and big data analytics as equivalent agents in the coming through of the social practice of strategy (Schatzki, 2001) and therefore theorizes strategy work as an effect of all arrays and dispositions of big data analytics and participants in strategy work (Callon and Law, 1997). As such, the text focuses on the constitutive dynamics between big data analytics and strategy actors and how they create agency and have performative implications for the reconstitution of new strategizing activities and outcomes (e.g., Akter et al., 2016; Barton and Court, 2012; Elia et al., 2019; Wamba et al., 2017).

For this purpose, the text ousts mental and linguistic representations from the way we think about big data analytics and condition its status as a passive object (Barad, 2003, 2007; Lemke, 2015). Instead, it magnifies the resistance of big data analytics to our modes of representation that bind its meaning to its role within the human context (Barad, 2003; Bennet, 2010; Crossland and Bauer, 2017; Harman, 2002; Latour, 2004b). The protean agent concept depicts big data analytics as something obdurate and in defiance of our interpretative frameworks (Rosiek, 2018) while also being constitutive of strategizing practices in the same way as strategy actors. As such, this discourse depicts big data analytics as vibrant and impulsive in seeking action and something that we discover as we inquire about it (Barad, 2007; Rosiek, 2018). Therefore, it is the entanglement between big data analytics and strategy actors in ongoing intra-activity that causes the emergence of the social practice and dynamics of strategizing.

Accordingly, big data analytics carries its meaning within its materiality and refutes our biased unitary view of it as a passive thing that awaits our cognitive or symbolic representation to reveal its being (Barad, 2007; Bennet, 2010; Rosiek, 2018). However, the text conceiving of big data analytics as a protean agent is an imperfect representation because, in certain passages, the text deprives humans of intentionality and "reconstitute(s) the ideal" (Grandy and Mills, 2004, p. 1161) by conferring agency on big data analytics (Latour, 1993, 2004a). Then, at other times, the text swings to embrace the Cartesian dualism between (knowers) strategy actors and (objects to know) big data analytics.

This shift contradicts the text's uniformity premise that supposedly rejects the 'big data analytics/strategy actors' distinction in favor of their entanglement. In addition, it neglects to inquire about or revise the causality or significance of big data analytics beyond its mere existence as a byproduct of strategizing activities—produced by cognitive or symbolic structures that drive human action and interactions (Reckwitz, 2002a, 2002b)— which in turn begets an asymmetric view of big data analytics and strategy that conceives of big data analytics as an object of reference that does not exist of itself but as an object strategy practitioners know, interpret, or talk about (Reckwitz, 2002a).

This object of reference concept shifts attention toward humans and their symbolic orders (mind, discourse, communication), which give big data analytics its symbolic quality and make it visible (Reckwitz, 2002a; Schatzki, 2001, 2005). This view supplants big data analytics with the human symbolic orders that refer to it and makes its reality simpler to understand. It advances the idea that big data analytics can be understood by humans through their mental or linguistic representations. Accordingly, the object of reference concept gains its symbolic quality at the level of cognitive (conscious/unconscious) structures that reside in the mind (Reckwitz, 2002a) and influence what can exist as an object of reference (e.g., Hasan and Gould, 2001; Heinrichs and Lim, 2003; Seddon et al., 2016; Shollo and Galliers, 2015; Thomassin Singh, 1998; Zamani, Griva, Spanaki, O'Raghallaigh and Sammon, 2021).

Similarly, symbolic orders outside the mind in extracognitive symbolic structures (discursive or textual) also can refer to big data analytics and therefore produce it (e.g., Neugarten, 2006; Pröllochs and Feuerriegel, 2020; Roth, Schwede, Valentinov, Pérez-Valls, & Kaivo-oja, 2019). Finally, symbolic orders in language-based social interactions (Reckwitz, 2002a, 2002b) can interpret big data analytics and constitute it in interactions to give it meaning (e.g., Aldea et al., 2018; Chen et al., 2015; Druckenmiller and Acar, 2009; Elbashir et al., 2011; Gu et al., 2021; Popovič et al., 2012). As such, the object of reference is a concept that gives humans primacy in handling big data analytics and thus in enacting big data analytics' affordances to supplement the doings of strategy (Reckwitz, 2002b; Schatzki, 2001, 2005).

Thus, big data analytics is objectified as a supplement to the social practice of strategizing, not a cause or a condition of its emergence (Derrida, 1976; Reckwitz, 2002a). Therefore, the systems of meaning (mind, discourse, communication) give big data analytics its symbolic quality and make it visible (Reckwitz, 2002a). This symbolic quality "bears no resemblance to reality" (Grandy and Mills, 2004, p. 1163) because it "displaces, colonizes, and thereby anticipate(s)" the real big data analytics (Baudrillard, 1994, p. 122; Gephart, 1996, p. 213); therefore it is no longer possible to "isolate the process" of big data analytics or to prove it (Baudrillard, 1983, p. 41). By so doing, the text contradicts its essential view of uniformity and entrenches the view of social practices as normative regularities, asymmetrical across its solid and stable constituents, and conditioned by habits and routines rather than by the social dynamics of strategy actors and big data analytics (Callon and Law, 1997).

In this view, only strategy actors hold the site of practical understanding and the capacity for action (Callon and Law, 1997), whereas big data analytics is restricted to practice, that is, it materializes within it; not outside it (Reckwitz, 2002b; Whitford and Zirpoli, 2014). Consequently, to explain the big data analytics and strategy relationship, the text necessitates tapping into humans' variables and attributes rather than the struggles associated with big data analytics as they undertake strategy work along with strategy actors (Pickering and Schatzki T, 2001).

5. The way forward: from disjointed to conjoined relationality

5.1. Disjointed relationality between big data analytics and strategy

5.1.1. The input-output discourse

The production system like input-output discourse signals covert distinct themes or 'double-entendres' underlying the text. Accordingly, the two active verbs 'replace' and 'emerge' entail two deviations from the literal sense of ordinary technical jargon to induce a rhetorical or vivid effect in the text as both verbs are 'evolutionary' metaphors.

First, 'replace' is a metaphor that pictures the non-data-savvy human as a substitutable element of the organization that cannot defeat the superiority of automation technologies. Second, the other direction of the 'emerge' metaphor entails the survival of the fittest or Darwin's natural selection, whereby those who are better adapted to their new strategizing context will survive. Both verbs identify with painting the picture of non-data-savvy and data-savvy humans participating in an active, on-going, and inevitable process of evolutionary survival of the 'fittest', which in turn knocks down the overt meaning of organizational alignment that the text lays out.

As such, the text fails its single determinant logic when it adopts an equifinality argument (Baldwin, 2019) that focuses on how to incrementally innovate organizational routines to keep pace with big data analytics' rapidly changing character and avoid a state of inertia that would require a radical alteration of the ingrained culture and routines (e.g., Merendino et al., 2018; Rohrbeck, 2012; Vecchiato, 2015). By so doing, the text shifts to exploring the factors impacting the technological advancements brought by big data analytics and how organizations can harness constant technological innovation to integrate their routines, both to deliver sustainable competitive advantage and fully exploit big data analytics to reposition themselves in the competitive environment (Beal, 2000; Cooper et al., 2000; Urbinati et al., 2019).

As a result, the text is silent on the relationship of big data analytics and strategizing and misses the underpinnings of this mutual influence. In fact, the way that big data analytics relates to structure is discontinued in favor of a race against time to derive better performance and value from its technological innovation (e.g., Dahiya et al., 2021; Ghasemaghaei and Calic, 2020; Guo et al., 2017). However, rejecting or endorsing a single determinant logic hinders taking big data analytics seriously and restricts the theoretical challenge. That challenge reappears whenever the firm's technological progress accelerates and has two poles: either big data analytics exerts an inexorable influence on organizations, or it holds 'clay' features that allow organizational actors to model and shape it as they see fit (Bodrožić and Adler, 2018; Davis, 2016; Faraj and Pachidi, 2021; Orlikowski, 1992).

In one respect, endorsing a single determinant logic highlights the following limitations. First, the importance of big data analytics as a determinant of structure dwindles when confronted with rhetoric that views organizational size and hierarchy as the only decisive factors in shaping structure (Donaldson, 2001), which necessarily replaces theoretical progress emphasizing big data analytics—"-which had virtually died out as a theme in the study of organizational form and function within the organization science literature" (Zammuto et al., 2007, p. 750, p. 750)—with theorizing that emphasizes subjects such as "power, institutions, human relations or transaction costs" (Faraj and Pachidi, 2021, p. 5). Second, there is a complication with containing big data analytics as part of existing theory arising from it being a construct conceptualized in different ways, which tends to relegate it to the background as a prop (Faraj and Pachidi, 2021). For example, when (Williamson, 1988, p. 375), the father of transaction cost economics, was asked about the place of technology in his theory, he responded: "technology thus serves to delimit the feasible set, choice within which mainly reflects transaction cost economizing purposes."

Similarly, the text draws from institutional theory to pay more attention to new institutional (re)orderings that are key for successful big data analytics transformations and investigate how these (re)orderings cultivate social acceptance (Hinings et al., 2018). As a result, the text finds it hard to deal with "the constitutive entanglement" of big data analytics and strategy, because its focus is toward epistemological standards whereby it infers to the "loveliest explanation, and so orient themselves to the explanation that provides theoretical elegance, confirmation of previous frames, or unified understanding", and frequently rejects "the likeliest explanation for it may appear to be more trivial, direct, and less aligned with paradigmatic assumptions" and therefore "no matter how fast [big data analytics is] transforming society and organization, [the text does] not rise to the level of theoretical loveliness" (Faraj and Pachidi, 2021; Lipton, 2004).

Nevertheless, rejecting the single determinant logic leads the text to fall prey to the very same assumptions it dismisses as inappropriate. First, establishing the belief that big data analytics is not what shapes structure denies it all agency and portrays it as a malleable artifact formed by the choices of managers (Faraj and Pachidi, 2021). This is despite the abundant evidence of the capacity of big data analytics to influence the social realm at the macro level and assist the social dynamics at the micro level (Misa, 1994). Second, a rejection of the single determinant argument instills a reluctance to value big data analytics because of its blurry ontological and epistemological position. This leads to questions around whether the focus should be on big data analytics as a computational capability or on big data analytics as an advanced sum of technologies, and whether to engage with big data analytics at the organizational, business unit or boundary spanners-level (Goodman and Sproull, 1990).

Third, when the text rejects the influence of big data analytics on structure, it still has to decide how to go about approaching the notion of big data analytics. It might approach the concept as a structure to be 'reciprocally engaged' with, given its ability to shape 'interaction patterns'(Barley, 1986; Orlikowski, 1992), or as something with the effect of a 'pun', capable of having more than one meaning, thus establishing entrenched 'interaction patterns' or unsettling them (Weick, 1990). Finally, the positivist epistemology of the input-output discourse embraces the pendulum movement of the text between single determinism and equifinality arguments. It also fails to add a new variable to strategy—the nature of the big data analytics—strategy relationship. All in all, the text maintains its silence about the big data analytics—strategy couplet by settling for big data analytics as an element that can influence strategy (Boudreau and Robey, 2005), and at the same time as subject to 'managerial choice', which models its usage to improve operational excellence and create and capture value (Daft, 2009, p. 20). As a corollary, the input-output discourse neglects to open up space for new theories or alternatives to its inherent positivism.

5.1.2. *The entanglement discourse*

Notwithstanding the text's fervor in promoting and encouraging the alignment and integration of big data analytics into strategizing practices and activities, we surmise that the prescriptions laid down to ensure the 'sociotechnical fit' and the recommendations for 'shared learning' and 'feedback loops' between non-data-savvy strategists and data scientists on the one hand, and analytical culture and deep structure on the other hand are inconsistent and contradictory vis-à-vis power distribution across these actors and regarding silent affordances enacted 'in situ' and the degree to which strategizing participants cause the shaping of these affordances and the social dynamics that orchestrate their encounters with big data analytics. The text suggests 'diffusion' of big data analytics across all layers of an organization to curb the potential inertia of the 'deep' social structure (Ardolino et al., 2018; Chen et al., 2015; Ciampi et al., 2021; Druckenmiller and Acar, 2009; Elbashir et al., 2011; Mikalef et al., 2019).

This advocacy, nonetheless, finds rebuttal in its very same roadmaps for tweaking the 'complex' social milieu of the doings of strategizing activities, and the 'training' and 'recruiting' prescriptions put forward to reconstruct the modus operandi of strategizing actors in accordance with the technological advancements of big data analytics (Akter et al., 2016; Barton and Court, 2012; Davenport and Barth, 2012; Knabke and Olbrich, 2017; Seddon et al., 2016). As such, the text approaches the big data analytics—strategy relationship with a presumed dichotomic binary relationship between big data analytics and its obtuse dynamics, which in turn yields a discourse ambiguous in its feelings toward the arrangement of relations between the elements of strategy practice. For instance, non-data-savvy strategizing practitioners appear 'so yesterday' and are represented as 'persona non grata' possessing obsolete skills, expendable 'gut feelings', and the ability to disturb the course of change, while data scientists are portrayed as oracles acting as a medium between executives and the complex wilderness of unstructured data, and through whom advice is sought to reflect upon what happened and what is ahead, thanks to their impartial analytical judgment and their dexterity in writing codes and machine learning algorithms (e.g., Arefin et al., 2015; Brinch et al., 2020; Kiron et al., 2014; Mazzei and Noble, 2017; Surbakti et al., 2020).

The text's rhetoric to encourage 'diffusion' of big data analytics into the doings of strategy relegates those involved in these activities to the background and brings to the fore the 'dialogue' between executives and data scientists who arise as 'trustees' that oversee strategy work. This inconsistent view of the control of the social dynamics of strategizing reflects an inherent uncertainty over the power relationships of data scientists and strategists in sharing duties and liabilities over strategizing activities. This opposition grants data scientists the untenable 'driver's seat' to challenge the 'deep' structure of strategizing from the investment in big data analytics until the latter reaches maturity, i.e., full diffusion throughout the social dynamics of strategy work, while it pictures non-data-savvy strategists as a 'standing reserve' to unquestionably comply with the new social order and participate in its alignment with existing practices through constant feedback, learning new skills, and redefining their functions (e.g., McAfeeand Brynjolfsson, 2012; Vidgen et al., 2017).

Our deconstructive analysis notes that this opposition reinscribes the same inertia it sets out to dissolve by enacting positions that foster an atmosphere of disputes and deadlocks where interactivity and collaboration fade away. The inexorable occurrence of big data analytics in the social practice of strategizing is based on having the players and the context of strategizing acquiescent and acclimatized to the progressive advancement of big data analytics. As such, the text proceeds with the portrayal of the social condition as a foregone conclusion and draws from the classical 'material/social' dualism to nurture a strict binary relationship of the big data analytics—strategy couplet following two orthogonal opposites: data scientists vs. strategists and deep structure vs. new data culture.

In the preceding part, we have exposed how the 'non-data-savvy' strategists are dismissed in favor of the 'data-savvy' participants and 'automated' processes. The text is emphatic about reaffirming this dichotomy by causing the reader to think that it is incumbent upon the 'non-data-savvy' to update their skills to match the needs and demands of big data analytics, while it simultaneously maintains a silent tone regarding the need to upgrade the features of big data analytics to account for the affordances enacted during strategy work. In this context, the roles that define participation in strategy work will change as big data analytics experts take over thanks to their skills that perfectly match the needs of big data analytics, and IT departments shift from managing data to becoming active participants in strategic development processes (e.g., Audzeyeva and Hudson, 2015; Kunc and O'Brien, 2019; Lavalle et al., 2011).

In the meantime, the text notes that failure to reap the benefits of big data analytics also could be due to the lack of motivation and unawareness of the 'non-data-savvy' referred to this time as 'staff' to denote the 'assistive' nature of their new role and their lack of understanding of the 'nitty-gritty' nature of unstructured data which leads their organizations to become 'analytically challenged' (e.g., Conboy, Dennehy, & O'Connor, 2020; Fosso Wamba, Akter and de Bourmont, 2019). In contrast, the text confers upon the data-savvy or data scientists the adjective 'practitioner' or 'actor' to signal their 'active engagement' in the strategizing activities, thanks to their polyvalent skills that span deploying and maintaining big data analytics infrastructure and understanding strategic issues and framing analytical solutions (e.g., Fink et al., 2016; Gupta et al., 2014). In addition, their 'expertise' also grants them leadership of these activities and the responsibility to 'weave' big data analytics into the 'story' of the organization (e.g., Conboy, Dennehy, & O'Connor, 2020; Fosso Wamba, Akter and de Bourmont, 2019).

Along with this responsibility, their new status demands the authority to oversee, recruit, and deploy talent to achieve the optimal synergy between the practice of strategizing and big data analytics toward value creation (e.g., Audzeyeva and Hudson, 2015; Pappas et al., 2018). However, the text frequently acknowledges the role of multigroup interactions in the integration of big data analytics across organization layers due to their support of dynamic alignment between big data analytics, its in-house or third-party providers, and its organizational users (e.g., Brinch et al., 2020; Shi and Wang, 2018). Paradoxically, the text implicitly foregrounds interaction in a sort of pledge of 'leaving no one behind' as a 'second route' to constructive deployment to ensure that those who 'fail to use big data analytics don't fall off the analytics' wagon (Fink et al., 2016).

This imagery transfers the reader to John William Waterhouse's painting "Consulting the Oracle" where the 'non-data-savvy' strategists seem like the seven women sitting in a ring opposite the standing lady, akin to the data scientist, who is giving them an account of the words of the deity or the oracle.

This sought-after devotion and attention of 'non-data-savvy' strategists to the new practices of big data analytics instill the difference of meaning between data scientists and non-data-savvy strategists whose meaning is deferred to a later time as the nature of what they do and what characterizes their qualities and features is put off. On the other hand, the text records nothing on the reasons that may privilege data-savvy strategists in their encounters with big data analytics, which betrays a character of condescending superiority vis-à-vis their role whose meaning is supplementary to that of data scientists.

This unexplained silence regarding their agency is baffling considering that they are the ones who, in contrast to data scientists, concentrate primarily on strategy work activities involving detailed and authoritative knowledge of their doings, routines and structures. Accordingly, the text maintains a supplementarity of meaning between data scientists and non-data-savvy participants to strip away the social practice of strategizing from its intricacies and relegate non-data-savvy participants to a supportive role. Conversely, the text explicitly calls for interaction and alignment to curb its cautious distrust toward organizational structures, as captured with the word 'deep' to describe an arrangement that is both obliging and rigid against change.

The text also invokes the 'house' metaphor to refer to this 'deep' structure. Sometimes the text seems at odds with its passive narrative vis-à-vis structure and occasionally depicts it as a challenge that big data analytics should and can adjust to over time and through feedback cycles that supposedly seek to decipher assumptions preadoption and postadoption of big data analytics (e.g., Audzeyeva and Hudson, 2015; Chen et al., 2015; Dokhanchi and Nazemi, 2015). Other times, the text hints at the unavoidable confrontation with the deep structure that might engender 'silos' that could hinder the maturity process of big data analytics (e.g., Brinch et al., 2021; Venkitachalam and Ambrosini, 2017). Similarly, the text glosses over the idea of authority and governance to diffuse the analytical culture across the organization to make it a 'data-driven' culture (e.g., Mikalef et al., 2019; Mikalef et al., 2020; Mikalef et al., 2021).

5.2. Conjoined relationality between big data analytics and strategy

5.2.1. Semiotic agency

The 'how' of strategy is the question that drives the agency divide between big data analytics and strategizing activities and practices via two foci. Asymmetrical agency understands strategizing as starting from the realm of deliberate and intentional activity and moving to the sequence of occurrences (Van de Ven, 1992) and the experience of practitioners and processes (Burgelman et al., 2018; MacKay et al., 2021), which ultimately prevents firms from accomplishing their intended strategy (Sminia, 2009). Such processes are macrolevel and include any organizational phenomena including "characteristics, processes, and behaviors … such as organizational capabilities and strategies" and organizational outcomes "related to the achievement of organizational goals such as strategic change, competitive advantage, and performance" (Kouamé and Langley, 2018, p. 561; see also Salvato and Rerup, 2011).

In contrast, symmetrical agency implies the performative aspect of strategy, that is, constituted and formed by the actors and big data analytics entanglement in the doings of strategy (Kornberger and Clegg, 2011; R. Whittington, 2006; Whittington et al., 2011).

Those doings are disclosed via the adoption and usage of big data analytics and represent the milieu where the symmetrical agency of big data analytics and strategy occurs and therefore tracing strategy to these doings emphasizes the constitutive role of microlevel processes (doings) in organizational objectives at the macro-level (realized strategy) (Baptista et al., 2021; Jarzabkowski, 2004; Jarzabkowski et al., 2007; Jarzabkowski and Wilson, 2006; Whittington et al., 2006).

Therefore, recovering the agency divide between big data analytics and strategy faces the challenge of connecting the local-level processes and practices of ground-level teams and individuals to the broader business strategy, organizational capabilities, and performance outcomes (Johnson et al., 2007; Pettigrew et al., 2001; Szulanski et al., 2005). This exercise behooves us to circumvent "perennial discussions of the relative priority of individual agency and social or cultural structures" (Rouse, 2006, pp. 645–646) through an alternative theorizing of relational agency between big data analytics and strategy as a matter of the underlying invisible patterned consistency immanent in the inadvertent propagation of data. It begins with the premise that the nature of reality follows semiotic relationality, and it is this view that reconceives of big data analytics and strategy as signs of "complex bundles of coordinated processes" (Rescher, 1996, p. 49) and accounts for the historicity and contingency of big data analytics without reducing it to the human context of discourse and linguistic representation or restricting it to a mediative role (Crossland and Bauer, 2017; Keane, 2003; Queiroz and Merrell, 2006).

By so doing, this semiotic relationality is what dissolves the agency divide between strategy and big data analytics because it views agency and thought as semiotic (see Table 1) and therefore does not anchor the relationship of process and doings in micro and macro or process—doings dualistic logics, but rather demolishes these very same dualistic distinctions to uncover the way "local coping actions aggregate and congeal into broader sociocultural practices that then provide the patterned regularities facilitating the possibility of strategy emergence and ultimately shaping organizational outcomes" (MacKay et al., 2021, pp. 1346–1347). Therefore, semiotic relationality does not divide the micro and the macro levels of strategizing, nor does it separate the strategist from big data analytics, and therefore, it does not distrust big data analytics and reduce it to its properties and affordances.

Instead, semiotic relationality surmounts these issues by forming the big data analytics—strategy relationship into a concept that is as "immanent in established" strategizing doings as "olive trees are imminent in olive seeds" (MacKay et al., 2021, p. 1351), which without interruption, moves strategy "toward its eventual condition" (Rescher, 1996, p. 11) of coming into view in the process of its realization as an olive tree.

Put differently, immanence is a predisposition, a modus operandi spread and promoted, without intention, via habitual and entrenched practices of individuals acting as a group. It is a certain nurtured sensitivity vis-à-vis the local milieu, a method of connecting with it, and a favored mechanism for becoming involved in and reacting to its nature—"what is or is not", that is, its "patterns, structures or properties" (Goldstein, 1999), without recourse to "deliberate intention" or planning on the part of either notion of the big data analytics—strategy couplet (Chia and Holt, 2009).

5.2.2. Semiotic causality

Since Aristotle, philosophers have developed a pluralistic understanding of the concept of causality that comprises four kinds of causes whereby change occurs. By means of illustration, material cause is what defines the structure and process of big data analytics. Second, efficient cause is every modification and upgrade of big data analytics technologies and affordances that designers and users deploy to create and develop its structure and process. Third, formal cause is the scheme followed in the aforementioned development process of big data analytics. Fourth is final cause, which is the purpose or intention of the process, that is, creating a system "for the sake of which" we understand what has happened, explain what is happening, and predict what is about to happen (Deacon, 2006).

To think of this intention as a future state that generates a present state, one needs to avoid approaching intention in terms of physical causality; otherwise, they will end up 'pointing to an unopened black box'. The Chinese philosopher Lao Tzu hinted at this kind of cause in the eleventh verse of his classic text Tao Te Ching translated by Hohne (2009): "Thirty spokes share the hub of a wheel; yet it is its center that makes it useful. You can mold clay into a vessel; yet it is its emptiness that makes it useful. Cut doors and windows from the walls of a house, but the ultimate use of the house will depend on that part where nothing exists. Therefore, something is shaped into what is; but its usefulness comes from what is not". Accordingly, the empty space that makes the wheel's hub is what creates the possibility for the thirty spokes to make up the wheel and cause its potential usage. Causality here is not related to the Aristotelian phrase "the whole is greater than the sum of the parts" but denotes "constitutive absence" that emerges from the unusual circular connectivity of restrictions and influences and allows "certain distributional and configurational regularities of constituents to reinforce one another iteratively throughout an entire system … it is the hole at the wheel's hub" (Deacon, 2006, p. 124–146).

To understand the constitutive absence of the wheel's hub, one needs to think of it in terms of semiosis or experience, a nondeterministic inclination, a generative tendency toward an ideal form that connects agents (Rosiek, 2018), or as Latour (2014) puts it: the French word 'sens', not to be confused with the English 'sense', but can be understood through the word 'inclination'. Suppose we were to reposition a vector that has a horizontal direction to the right (keeping the vector the same by not rotating it). In that case, the vector could have multiple directions but only two inclinations: above or below the horizontal direction to the right. This inclination is what Latour (2014) means by sens, which represents the universal connector between human and material entities of life (Kohn, 2013; Latour, 2014; Rosiek, 2018). According to Peirce (1988), this inclination is a habit (human or material) that involves anticipation of future possibilities, that is, the Aristotelian 'esse in futuro' (see also Short, 2007; Rosiek and Snyder, 2018). Consequently, all elements of life (human and material) have an ideal (future) possibility, a habit, tendency, or purpose that shapes the becoming of their meaning (Short, 2007).

For instance, the tendency to write with a pen shapes its materiality; in the same way, the tendency to produce a palm tree shapes the material form of a palm tree seed (Rosiek and Snyder, 2018). An office space has a tendency to organize strategy practitioners into

Table 1
A semiotic view of big data analytics and strategy for recovering the input-output/entanglement divide.

<table>
<tr><th></th><th colspan="2">Disjointed relationality</th><th colspan="2">Conjoined relationality</th></tr>
<tr><th></th><th>Causality</th><th>Agency</th><th>Causality/Agency</th><th>Potential research topics</th></tr>
<tr><td>Entanglment</td><td>Intra-active causality
Between:
1. Practices 'embodied in all configurations that produce big data analytics'
2. Phenomena 'the relations of big data analytics produced'</td><td>Symmetric agency
Agency is a matter of an ongoing process of intra-activity and entanglement between:
1. A vibrant big data analytics that impels action.
2. Strategy actors who do not relate to big data analytics as an object of reference but via its performativity of the nature of practices.
Vs.</td><td>Semiotic causality
It resides in a form constitutive in its absence. Form is neither cognitive nor material but is an absential pattern that results from constraints on possibility.</td><td rowspan="2">• The ways big data analytics cause and alter strategy work's activities and practices.
• The role of big data analytics materiality and embodiment in new virtual means of strategy work.
• The ways big data analytics reconfigure/transform strategy work's boundaries.
• The ways big data analytics-strategy relationship can explain the enactment and change of strategy work.
• The different constraints on possibility in the doings of strategy with big data analytics.
• The interplay between big data analytics and strategists in outperforming one another in strategy work.
• The objectifying of strategy processes, practitioners, and big data analytics into indefinite relations.
• The interplay between power structure and big data analytics.
• The interdependencies between big data analytics and strategizing activities, praxies, and practices.
• How indefinite relations between big data analytics and strategy practitioners evolve over time and confront and reveal constraints on possible new and existing relations.
• The ways form patterns propagate through strategy practitioners & affects the logic of strategizing from within.
• The ways the forming patterns of strategizing practices emerge as effects of patterns of big data analytics.</td></tr>
<tr><td>Input-output</td><td>Mechanistic causality
It brackets the ends for which big data analytics exists, ascribing the ends out of which big data analytics comes to be following one of two directions:
1. The intervention of big data analytics into the social realm is one-directional and certain to occur.
2. The precedence of strategy actors over big data analytics in modeling its features and affordances & conducting strategy work.</td><td>Asymmetric agency
Separation between:
1. Strategy actors as the driver of social order and big data analytics is understood as gateways to their cognitive structures, discursive practices, and social interactions.
2. Big data analytics whose quality and purpose, following the course of technological advancements, can naturally determine and change the socio-organizational order.</td><td>Semiotic agency
It resides in intentionality. It is not connected through cause and effect but through a nondeterministic inclination that drives its folding direction toward an ideal form that connects agents.</td></tr>
</table>

the general form of a workshop, although the actual workshop will be a response to the interaction between the office space and the conditions imposed by the participants. Big data analytics has a tendency to organize data into a certain form of patterns, although the actual pattern data adopt will be an outcome of the interaction of data and the human-monitored analytical variables. An office space is as much about what is inside the walls as the absence they delimit. Accordingly, certain strategizing practices depend on what the office space is as much as all excluded absences that it is not.

This constitutive absence is not a material quality, it is a relation to a real that is not here as opposed to a real that is out there, which ignores the spontaneity of life, its tendency to emerge, not to mention its semiosis in which the human and material are nested (Bateson, 2000; Deacon, 2006). Limiting the real to what happens reinstigates the possibility of life in the mind, and does not account for how this mind could have emerged out of semiosis; nor does it account for how it relates to the semiotic chain in the human and material realms (Kohn, 2013). This real is what Peirce names secondness (CP 1.23, 26).[1] The apple dropping on Newton's head is secondness insofar as it is a "shocking" (CP 1.336), "brutal" (CP 1.419), event that disrupts our habituality and pushes us to think differently (Kohn, 2013; CP 1.336). However, Peirce does not limit the real to secondness, but extends beyond it to a much broader real that could encompass his semiotics and, therefore, a nondualistic view of our existence in relation to spontaneity and emergence (Kohn, 2013).

Peirce devises a triadic semiotic system for this endeavor, of which secondness is only one aspect. Firstness is the aspect that involves raw spontaneity, quality, feeling, in a vacuum, detached from anything else (Kohn, 2013; CP 1.304). Thirdness concerns the world's "tendency to take habits" of all entities in the universe, the tendency to have patterns, purposes, and regularities (Kohn, 2013; CP 1.409; CP 6.101). Thirdness does not occur in the mind, nor is it imposed by it; it is innate to the world: the generality that conditions semiosis (Kohn, 2013).

In the doings of strategy with big data analytics, form patterns proliferate to an unprecedented degree in all directions, yielding what Boyd and Crawford (2012) refer to as apophenia, that is, seeing patterns where absence prevails. Form here is not a synonym of structure or domain but is a process of pattern production and propagation whose innate generative logic comes to permeate humans as they harness it (Deacon, 2006, 2012; Kohn, 2013; Latour, 2014). These patterns are significant in their absence, akin to the dog that did not bark, whose silence helped Sherlock Holmes solve the mystery of the racehorse that had disappeared. During the investigation, a police inspector asks Holmes whether anything caught his attention, to which Holmes replied: "the curious incident of the dog." The inspector replied: "the dog did nothing that night." Holmes: "that was the curious incident … had grasped the silence of the dog for one true inference invariably suggests others … obviously the midnight visitor was someone the dog knew well" (Doyle, 1894, pp. 19–23). Floridi (2012) suggests that when these patterns are absent, that is probably also a curious incident akin to when data did not 'bark' prior to the subprime mortgage crisis of 2007–2010.

This form, constitutive in its absence, directs our attention beyond whatever emerges from the coupling of big data analytics and strategy and toward that which is not visible to reveal the secret workings behind the manifestation of the visible. For instance, Pickering (2001) references Schivelbusch's (1986) railway journey, where the human experience of the train created a new emergent phenomenon, 'panoramic seeing', that was not possible prior to the encounter. Through the description of the train journey, Schivelbusch (1986) reveals how the coupling of the human and train connected the traveler to new mental and bodily forms of a new subject, the panoramic observer beyond the object train (Pickering and Schatzki T, 2001).

Form is therefore an invitation to go beyond the causality divide of strategy and big data analytics to understand what drives strategy to emerge. Form propagates itself through strategy actors and affects the logic of strategizing from within. For instance, big data analytics turns data into form when it aggregates it from its unstructured messiness, yet aggregated data flow into strategizing activities to point to reality beyond them at the price of compromising the rich and complex distributive data that high abstraction overlooks and therefore convey dubious descriptions of reality (Constantiou and Kallinikos, 2014).

Seeing distributive data does not imply a shift of perspective, but the ability to see form twice; for both aggregate and distributive data are two dimensions of the same entity: one is the inside of the other, and either explains the other (Coutin, 2002). Therefore, the phenomenon at hand is not 'outside' that which is endemic to our encounters with material practices of strategizing, but is inherently 'inside' the absent patterns of strategizing practice. As such, the forming patterns of strategizing practices are the effects of self-organizing selves (Deacon, 2006, 2012), and to practice strategizing on the terms of these form patterns, to enter their relational causal logic, to account for their constitutive absences, it is necessary to become attuned to their existence and self-organizing nature and attend to rendering these self-organizing selves accessible from within, that is to say, turning the patterns inside out, akin to finding a vantage point from which one can attend to what seems too familiar to apprehend (Kohn, 2013; Riles, 2000).

6. Conclusion

The purpose of this review was not to offer an objectivist account of the big data analytics—strategy relationship. The content represents an expressly stated deconstructive perspective of its authors that seeks to open new avenues of inquiry into alternative views of big data analytics and strategy.

First, the form constitutive in its absence is neither cognitive nor material. It is an absential pattern that results from constrained opportunity and thus it is a hard notion to attend to ethnographically because it is ephemeral, hidden from our standard modes of inquiry, and does not have the tangible otherness of any ethnographic project (Kohn, 2013). Therefore, attending to form is embarking on a project akin to an ethnographic observation of a phenomenon for which we do not possess a methodological tool to create a description. The phenomenon at hand is not outside, that is, endemic to our encounters with the material practices of big data analytics and strategy, but is rather inherently inside the absent patterns of big data analytics. Therefore, the method should aim to flush out this constitutive form and illuminate how the constraints on opportunity emerge in the doings of strategy with big data analytics, the particular manner its patterns propagate, and the ways in which they come to matter to the practitioners of strategy. Riles (2000) describes this project as finding a vantage point from which to attend to what seems too familiar to apprehend. This method should thus aim to reveal that the forming patterns of big data analytics are the effects of the absence of self-organizing selves (Deacon, 2006, 2012), and future research should address rendering these accessible from within, that is, turning the patterns inside out (Riles, 2000).

[1] References to the works of Charles Peirce follow this standard form of citation used by Peirce scholars: the initials of the title of Peirce's work followed by the volume and paragraph numbers. CP stands for The Collected Papers of Charles Peirce.

Second, using the new conceptualization of big data analytics and strategy as part of semiosis, scholars can apply the instantiation method that involves engaging with the data comprehensively at the micro-level and over time to identify how microlevel big data analytics' constitutive absence evolves and becomes embedded at multiple levels of an organization and yields strategy emergence (Kouamé and Langley, 2018). Instantiation is a perfect fit for empirical studies investigating big data analytics' constitutive form because the method is grounded in practice theorizing, which holds that practices constitute the social world (Schatzki, 2001), and the connection between microlevel processes and macrolevel organizational outcomes as tacit and 'virtually simultaneous'. Therefore scholars can adopt instantiation, with its embeddedness logic, to demonstrate how big data analytics' form influences microprocesses to "directly instantiate or constitute the macroprocesses through which the organization exists or is changing" (Kouamé and Langley, 2018, p. 572).

Author statement

Yassine Talaoui: Conceptualization, Methodology, Investigation, Formal Analysis, Visualization, Writing, Review, Editing**. Marko Kohtamäki**: Supervision, Validation, Editing, Resources. **Mikko Ranta:** LDA, Software. **Sortirios Paroutis:** Validation, Editing.

Data availability

No data was used for the research described in the article.

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Appendices.

Appendix 1. Sample views of big data analytics

View	Focus	Papers
A technological resource supporting informed strategy planning/process/decision-making	Big data analytics & business activities	Roden et al. (2017) Gupta et al. (2017) Wang et al. (2016)
	Big data analytics & business value1	Muller and Jensen (2017) Wamba et al. (2015) Akter et al. (2016a) Sharma et al. (2014) Trieu (2017)
	Big data analytics: system/dimensions/applications/ evolution	Watson (2009) Chen et al. (2012) Jourdan (2008) Eom (1996; 1998) Eom and Kim (2006) Arnott and Pervan (2005; 2008, 2012, 2014) Abbasi et al. (2016) Sivarajah et al. (2017) Bose (2009) Shim et al. (2002) Moro et al. (2015) Harrison et al. (2015) Kwon et al., 2014 Khoong (1995) Hosac et al. (2012)
A capability innovating strategy making/business models		Boyd and Crawford 2012 Bharadwaj et al. (2013) Mora et al. (2005) Holsapple et al. (2014) Bacic and Fadlalla (2016) Mikalef et al. (2017)
	Big data analytics & firm performance/competitive advantage/business models innovation	Gupta and George (2016) Loebbecke and Picot (2015) Davis (2014)

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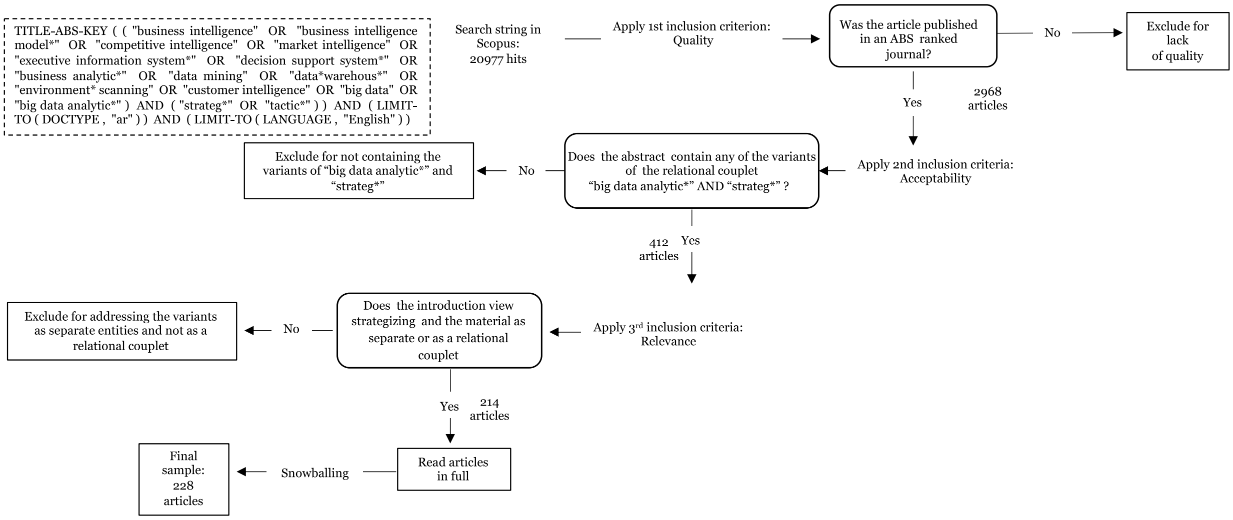
View	Focus	Papers
		Davenport et al. (2012) McAfee et al. (2012) Opresnik and Taisch (2015) Kim et al. (2012) Kiron et al. (2014) Mikalef et al. (2020)

Appendix 2. Systematic search process of the literature



Appendix 3. A step-by-step reporting of the mixed methods design (adapted from Aranda et al., 2021)

Steps	Activities & Results
Step 1: Establish theoretical focus	Activity 1: Inform choice of texts to be included in the corpus Ou research question "In what ways are strategy and big data analytics depicted as related concepts in the literature?" informs our choice of texts to be included in the corpus. Activity 2: Identify articles addressing the relationship of big data analytics and strategy Our review follows a systematic protocol to give a sense to other researchers of our exclusion and inclusion criteria (Lee, 2009; Tranfield, Denyer and Smart, 2003), and carry our arguments based on a scientific empirical synthesis (Rousseau, Manning and Denyer, 2008) that offers relevant contributions to both strategy and information systems scholarship (Macpherson and Jones, 2010).
Step 2:Extract textual corpus	Activity 1: Collect search strings We combine search strings that capture the relational couplet 'big data analytics—strategy' from previous reviews on big data analytics. Following Mackay and Zundel (2017), we include the concepts 'strateg*' and 'tactic*' rather than practice because scholars often use this latter to refer to both concepts (De Certeau, 1988; Scott, 1998), or as a synonymous for strategy (Johnson, Langley, Melin and Whittington, 2008). Activity 2: Conduct search process Appendix 2 summarizes our search process involving compiled search strings across titles, abstracts, and keywords of publications on Scopus database. We include asterisk* and Boolean operator OR to account for all variations of keywords, and Boolean operator AND to consider only the articles that address the relationship between any conceptualization of strategy and big data analytics. After we elaborated our search string, we undertake a search on Scopus for all publications that apply to our relational couplet. Although these criteria limit the sample, their imposition was necessary as our search on Scopus returns 20977 hits (Mackay and Zundel, 2017). We seek to include only articles published in the 1709 journals of the 2021 Academic Journal Guide (AJG) because this ranking offers an extensive cross-disciplinary list of journals subject to a documented hybrid verification and iterative ranking process based upon peer reviews, peers' consensus, and citations (Mingers and Willcocks, 2017; Morris, Harvey and Kelly, 2009), which gives us a credible guide to account for the quality standard necessary for developing a high-quality literature synthesis (Macpherson and Jones, 2010; Rousseau et al., 2008). This criterion returns 2968 articles whose abstracts we read to identify 412 articles where both variants of the relational couplet "big data analytics—strategy" appear. As we read all introductions, we excluded articles that do not engage with the relationship of big data analytics and strategy or refer to strategy in passing, if we could substitute their strategy verbiage by any other adverbial utterance to convey importance without jeopardizing the spirit of the article (Orlikowski and Iacono, 2001). This reduced our

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Steps	Activities & Results
	sample to 214 publications which we read in full and expanded to 228 articles after we came across other contributions as we read the articles and checked their citations and lists of references (Lee, 2009).
Step 3: Specify topics	Activity 1: Determine the number of topics Once we identified our corpus, and before running LDA, a crucial step was to determine the number of topics we were going to choose. Statistically, there is no way to decide the right number of topics that best describe a given textual data set (Aranda et al., 2021). Both Roberts et al. (2019) and Aranda et al. (2021) recommend a rigid search over a likely set of topics. The scope of the grid search relies upon the number of articles to be examined and the research question that dictates the depth of the analysis (Aranda et al., 2021). Although in previous studies the number of topics appears to be as low as 12 and as high as 200 (DiMaggio et al., 2013; Puranam et al., 2017), it seems that the rule of thumb is "the larger the number of documents and the higher the level of detail required, the more topics are needed to capture the corpus' thematic content adequately" (Aranda et al., 2021, p.204). To identify the sets of topics in our sample, we increased the value of eta to 1, based on Fligstein et al. (2017), to allow for neutral prior distributions and expose the dominant topics based on data rather than our assumptions. Following Wallach, Mimno, and McCallum (2009), we use asymmetric prior LDA to automatically learn the asymmetric prior distribution from the data, a setting that gives the best results with LDA (Huang, 2005). Besides, we draw from Steyvers and Griffiths (2007) in removing repetitive words that appear in more than 90% of documents to remove most 'filler' words that carry no relation to topic content and differences across documents. Our aim was to slice the data into the smallest possible details without compromising the coherence of topics. We started with 20 topics and using the search () function of the Structural Topic Modeling (STM) library, that identifies the optimal number of topics using the semantic coherence measure of the STM library and subjective evaluation, we ended up with 34 topics. This topic sample seems coherent with the literature suggesting that topics below 100 are more desirable as they uncover most discriminating topics (Schmiedel et al., 2018), i.e., "those characterized by distinct top identifying words" (Aranda et al., 2021, p.204). Activity 2: Make sense of bags of words On the grounds of deconstructive discourse analysis, once LDA identified the topics, we made sense of "the bags of words" linked with each topic–because "word associations" with each topic are crucial to labeling topic—by re-reading the set of most representative articles for each topic to develop a thorough and critical understanding of the articles in light of the research questions and theoretical focus identified in step 1 (Aranda et al., 2021, p.204).
Step 4: Uncover discourses	Activity 1: Explore discourses After we identified and interpreted the 34 topics, we further explored their relations in order to obtain discourses, i.e., "broader meaning structures" (Aranda et al., 2021, p. 205). For this endeavor, we availed ourselves with a visual graph that illustrates the network of topic relations and the probability of topics being addressed together or distant from one another (Aranda et al., 2021). We built the visual graph using the STM library of the R language (Roberts et al., 2019), and drew connections across topics based on correlations between the word weights of topics. The correlations higher than 0.05 are represented with dashed lines that are drawn using the ordinary (Pearson) correlation metric between topics. Activity 2: Identify evolution of discourses Fig. 2 presents the correlation graph for the 34 topics and helps us understand the linkages across these topics and examine whether these topic linkages could be aggregated into broader discourse clusters (Aranda et al., 2021). Two main discourse clusters emerge via topic linkages: on the left part, a cluster around big data analytics that mediate the descriptions of strategy context (input-output discourse); on the right, there is a cluster around the social consequences of big data analytics that mediate the reshaping of strategizing activities (entanglement discourse). These two discourse clusters represent a comprehensive discursive profile characterizing the debates around strategy and big data analytics. Moreover, to identify the evolution of the two discourses over time, we visually examined their time dynamics on the second part of Fig. 2, which indicates the aggregate proportion of each discourse in the textual corpus. These aggregate lines were drawn by adding the weights of individual topics for the two discourses insofar as the two trendlines will add up to one. This step is necessary for identifying key moments of interest and usage in the life of each discourse (Aranda et al., 2021). It tells us that a negative correlation is what drives the way the two discourses evolve in the debates around the 'big data analytics—strategy' couplet, insofar as their relation is an opposite changing one. For instance, when the discourse on big data analytics as computational capability representing strategy context (input-output discourse) peaked in 2000, the interest in the discourse on big data analytics as a socially constructed agent that (re)shapes of strategizing activities (entanglement discourse) was at its lowest.
Step 5: Choose a sample to zoom in on	Activity 1: Qualitative analysis At this stage, we selected all texts from the most representative articles of each discourse for qualitative analysis. We use deconstructive discourse analysis strategies to interpret these texts that represent "structuring moments" (Aranda et al., 2021, p.206) within the debates shaping the strategy and big data analytics. In practice, we focus on the two discourses and inspect the full content of the most representative articles (title, abstract, keywords, full text, figures, tables, etc). Our unit of analysis is the reader's experience with the text and do not inquire or seek to expose the intentions the authors had at the time of writing the articles because on the terms of deconstructive discourse analysis, each article compiles knowledge that reflects the work of a certain context and many unknown people whose aims and intents are silent (Beath and Orlikowski, 1994; Norris, 1991).
Step 6: Code selected texts	Activity 1: Qualitative coding This step of the model is concerned with the coding strategies of texts and their ensuing interpretations (Aranda et al., 2021). Contrary to previous applications of deconstructive discourse analysis in organization and management studies, which focus on polished and praised scholarly and literary opuses and therefore expose their distinctive literary or artistic appearance, our sample is a cross-disciplinary one whereof many papers are neither conceptual nor literary. As a corollary, our deconstructive discourse analysis disregards any absence of elegance in writing, sophistication in logical processes, or robustness in evidence (Beath and Orlikowski, 1994). Deconstructive discourse analysis is an endless examination of text and therefore we do not hold our inquiry as the sole deconstruction of the body of knowledge on the big data analytics and strategy relationship, but ours pays particular attention to the relationship between the two elements of the couplet, and therefore other researchers can concentrate on deconstructing other subjects of the sample or continue deconstructing our own text or interpretations (Beath and Orlikowski, 1994). Our aim is to question the self-defining origins of the two discourses that persist throughout the literature (Rasche, 2008) to determine the state of occurring of "… dichotomies, contradictions, disruptions, naturalness claims, silences, marginalized elements, metaphors, and double-entendres …" (Beath and Orlikowski, 1994, p. 357). For illustration, Appendix 3 reports our coding analysis for both discourses following deconstruction strategies from Martin (1990)

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Steps	Activities & Results
	and Beath and Orlikowski (1994). These coding strategies are essential in refining theoretical interpretations of LDA results, which on their own would not have divulged the taken-for-granted assumptions, dichotomies and implicit meaning in the text. Appendix 6 lays out our interpretation along with some examples of textual excerpts that corroborate our deconstructive analysis.
Step 7: Develop findings & generalizations	Activity 1: Integrate quantitative and qualitative analyses To further bolster our analysis with an additional layer, we integrate insights from LDA and deconstructive discourse analysis. First, we explore in detail how the two identified discourses (see Fig. 2) nurture the debates on big data analytics and strategy. Next, we analyze each of the discourses in turn, based on textual evidence coded using deconstructive strategies (see Appendix 3). Our aim is to question the self-defining origins that are represented by the two discourses that persist throughout the literature (Rasche, 2008) and expose their inherent dichotomies that prevent complementarity. Activity 2: Acknowledge limitations First, the review data comprise scientific articles systematically retrieved from the Scopus database. Therefore, some articles may have been left out from the final samples because of the usage of different keywords, terminologies, concepts, or because those articles were published in other databases. Considering that the review accounts for articles published up to December 2021, articles in press after this date may also have been overlooked. Second, the deconstructive account of 'big data analytics—strategy' relationship is subject to the authors' own interpretations. On the grounds of post-structuralist deconstructive discourse analysis, each scientific text reviewed mirrors the preferred reading of its authors. An article therefore begins by identifying its particular discourse, not as an end but as a means to disclose the points of rupture where the text's constitutive elements unravel, only to pinpoint other non-preferred readings to question what the familiar and certain meaning is (Watson and Wood-Harper, 1996; Willmott, 1994). Similarly, this review represents the preferred reading of its authors and therefore invites other deconstructive examinations in a series of challenges to its form and content, ad infinitum (Beath and Orlikowski, 1994). Third, the broad and cross-disciplinary scope of 'big data analytics—strategy' literature and the vast number of underlying assumptions, philosophical paradigms, and theories upon which each stream grounds itself make it the task of this paper to synthesize and deconstruct. That is a challenging undertaking, and therefore, this review may have overlooked or trivialized relevant divergences, dichotomies, and similarities between different views and perspectives that motivate the treatment of 'big data analytics—strategy' relationship. Similarly, the classifications, juxtapositions, and integrative treatments of scholars, theories, or streams can appear somewhat biased by the authors' interpretations and ontological and epistemological preferences.

Appendix 4. Most representative papers of the input-output discourse

The input-output discourse				
Topic	Top words	Issue	Focus	Most representative papers
3	plan, support, inform, process, use, group, gss, organ	Supporting strategic planning & organizational structure	Supporting strategic planning	Orwig et al., 1996
			Supporting strategic business objectives	Frolick and Robichaux, 1995
			Supporting strategic planning	Dennis et al., 1997
			Modeling & mapping distinctive competence	Eden and Ackermann, 2000
			Supporting organizational models	Migliarese and Paolucci, 1995
			Monitoring and scanning environment for strategic planning	Frolick et al., 1997
7	competit, strategi, model, inform, compani, enterpris, oper, can	Competitive analysis for strategy formulation	Informing competitive environment analysis	Liu et al., 2018
			Analyzing & modeling the competitive environment	Ding and Shi, 2021
			Scanning the environment for strategy formulation	Gershon, 2000
			Environmental assessment for competitive strategy selection	Lee and Lee, 2012
			Descriptive and supportive analytics for strategic objectives	Giacomazzi et al., 1997
			Prescriptive and predictive analytics to generate strategic map and strategic action plans	Wang et al., 2018
8	environment, scan, orient, firm, top, perform, goal, studi	Scanning the environment for strategic decision making	Executives goal orientation and scanning to achieve firm strategy and performance	Pryor et al., 2019
			Scanning to align competitive strategies with environmental requirements	Beal, 2000
			Determining importance of factors affecting strategic decision making under uncertainty	Li et al., 2009
			Impact of big data on firm performance	Ghasemaghaei and Calic, 2020
			Impact of strategic foresight on strategic adaptability to environment dynamism	Nyuur et al., 2015
			Big data analytics for real-time automated competitor analysis and firm position monitoring	Guo et al., 2017

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The input-output discourse				
Topic	Top words	Issue	Focus	Most representative papers
			Impact of executives' perception of the environment on strategy formulation & firm performance	Analoui and Karami, 2002
16	decis, method, model, system, weight, use, problem, altern	Smart modeling of intuitive and human judgement	An adaptive big data system to operationalize a due diligence scorecard model for adaptive strategies	Lau et al., 2012
			Developing a rational model for strategy evaluation	Tavana, 2002
			Proposing a computer led strategic decision-making architecture for strategic decisions	Bayrak et al., 2021
			Designing a long-term support system for strategic decision making	Van Groenendaal, 2003
			Building a multiple criteria system to evaluate strategic alternatives	Tavana and Banerjee, 1995
			Combining big data analytics and balanced scorecard for determining firm strategy	Tjader et al., 2014
			Designing a strategy map using big data analytics techniques	Quezada and Ospina, 2014
			Assessing the opportunities for applications of intelligence methods for strategic decisions	Gaidelys and Dailydka, 2016
17	signal, weak, inform, use, process, document, lter, term	Deciphering weak signals for strategic planning	Automated identification of weak signals for strategic planning	Thorleuchter and Den Poel, 2013
			Semantic tracing of weak signals for strategic planning	Thorleuchter et al., 2014
			Idea mining for strategic decision making	Thorleuchter and Den Poel, 2015
			Information filters' impact on environmental scanning process under uncertainty	Sheppard and Kuusi, 2013
			Filters of weak signals for pro-active strategy-creation process	Ilmola and Kuusi 2006
			Strategic radar system to enhance adaptive capability for coping with external change	Schoemaker et al., 2013
19	decis, action, scenario, system, agent, scenario, tion, set, portfolio	Scenario-based strategy development	Scenarios defining for proactive strategic actions	Vilkkumaa et al., 2018
			Multi agent for modeling strategic solutions	Pinson et al., 1997
			Artificial intelligent agents for data accumulation and sharing	Elofson et al., 1997
			Artificial intelligent agents for maintaining the cognitive model of the organization	Sillince, 1996
22	use, warehous, data, busi, system, inform, manag, decis	Data management for superior performance	Data management for decision support	Watson et al., 2006
			Integration, implementation, intelligence, and innovation of data warehouses to support strategy formulation, implementation, and evaluation	March and Hevner, 2007
			Creating an enterprise-wide BI capability to support corporate strategy	Wixom et al., 2011
			Data warehousing and BI as an integrated foundation for wide planning and strategy support	Dinter et al., 2010
			Examining the failures and success of BI implementations	Boyton et al., 2015
			Data warehousing as a means to competitive advantage	Cooper et al., 2000
			Integrating data mining techniques with business models for strategic performance capability	Heinrichs and Lim, 2003
			Big data analytics impact on value creation and capture	Grover et al., 2018
			Integrating business analytics into strategic planning for better performance	Klatt et al., 2011
			The role of the decision environment in how BI capabilities are leveraged to achieve success	Işik et al., 2013
23	use, industri, data, market, model, product, compani, rms	Analytics support for strategic planning	Multi-period optimization-based support of strategic planning (Aluminum company)	Dutta et al., 2011
			Multi-period optimization-based support of strategic planning (Pharmaceutical company)	Dutta et al., 2007
			Database structures for multi-period optimization-based support of strategic planning	Dutta and Fourer, 2008
			Simulate competitive environment and automate strategic decisions	Klein, 1999
			Generate and update market sensing-matrix for developing and implementing strategies	Kumar et al., 2020
			Increase the ability of analytics to support a broader range of corporate strategies	Price et al., 1998
			Mental modeling to scan the domino effects of patterns of change in the industry	McHardy, 1995

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Topic	Top words	Issue	Focus	Most representative papers
The input-output discourse				
			Determining the optimal mix of technology and strategy for decisions	Raisinghani et al., 2007
			Understanding competitors and monitoring rivals' strategies and tactics	Simkin, 1997
			The pattern and frequency of use of analytics by executives in their strategic decision-making	Ahituv et al., 1998
24	use, knowledg, manag, inform, compani, data, process, technolog	Integrating big data into strategy work	The relationship between big data analytics, firm-specific knowledge, & competitive advantage	Dahiya et al., 2021
			A dynamic capability perspective to the relationship between foresight and value creation	Rohrbeck, 2011
			Ensuring the continuity of big data system via cloud computing services	Tvrdikova, 2016
			The implementation and use of a intelligence scanning to identify innovation opportunities	Nilsson, 2012
			A theoretical framework on value creation and capture by relying on Big Data	Urbinati et al., 2019
			Integrating big data in the process of strategic management	Viitanen and Pirttimaki, 2006
25	environment, scan, inform, strateg, chang, extern, environ, manag	Data acquisition to curb environmental uncertainty	Scanning competitive and uncertain environment for business expansion strategies	Wu et al., 1998
			Intelligent agent to accomplish scanning tasks and provide up-to-date market information	Liu, 1998 a
			Intelligence collection and high environmental dynamism	Hough and White, 2004
			Intelligence collection and volatility of the environment and the diverse nature of businesses	Ngamkroeckjoti and Johri, 2000
			Probabilistic models for intelligence & attainment test to identify uncertain environment items	Rodriguez and Estevez, 2007
			Environmental scanning as a moderator of strategy–performance relationships	Davis et al., 2008
			Business environment scanning as strategic input into planning	Olamade et al., 2011
			The incidence and scope of scanning in the company's strategy formulation process	Jogaratnam and Wong 2009
			Strategic renewal over time through environmental scanning	Ben-Menahem et al., 2013
			Scanning model to anticipate changes and to improve the quality of strategic planning	Navaratnam and Scott, 1995
			Intelligence as the first link in the chain of actions that permit strategy formulation	Elenkov, 1997
			Scanning as a critical success factor for firm's strategy and environment uncertainty	Raymond et al., 2001
27	uncertainty, strateg, environment, scan, environ, perceiv, inform, organ	Environmental uncertainty as antecedent to data acquisition	The relationship between environmental uncertainty, intelligence scanning, and performance.	Sawyerr et al., 2003
			The relationship between perceived uncertainty and scanning frequency of executives	May et al., 2000
			The alignment of organizational contexts and the design of intelligence scanning systems	Ardekani and Nystrom, 1996
			The relationship between scanning and the tendency of strategies to focus on tactics	Miller and Toulouse, 1998
			The relationship between the importance, complexity of intelligence collection of executives	Boyd and Fulk, 1996
			The relationship between environment and intelligence scanning behavior of executives	Ebrahimi, 2000
28	foresight, futur, strateg, use, approach, research, vol,	Futuristic outlook for strategic planning	Designing a foresight capacity to strengthen strategy planning, development, and analysis	Voros, 2009
			Introducing foresight process framework into formal strategic planning	Voros, 2003
			Foresight approaches to improve organizational flexibility and alignment versus environment	Vecchiato, 2015
			Identifying indicators of emergency situations and changes in business structures	Nagel and Aviles, 2020
			Integrating big data techniques with network analysis to form an intelligence analysis model	Köseoglu et al., 2020
			A dynamic capability perspective to the relationship between foresight and value creation	Rohrbeck, 2011
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The input-output discourse				
Topic	Top words	Issue	Focus	Most representative papers
	decis, use, make, execut, manag, system, support, research	Use patterns of strategy practitioners	Big data issues arising from the discovery of cultural styles of strategic decision making	Martinsons and Davison, 2007
			A framework of BI use patterns for the development of high quality BI for strategic decisions	Arnott et al., 2017
			Intelligence support system requirements of senior executives	Arnott, 2010
			The adoption, use, and impact of intelligence support on strategic decision making	Elam and Leidner, 1995
			How strategists use big data to support internal business decisions, discovery and production	Davenport 2014
			How to turn big data into knowledge and then to results	Davenport et al., 2001
30	inform, intellig, competitor, competit, strateg, organ, manag, market	External intelligence to feed strategy planning and process	The usage of strategic intelligence as a strategic management tool	Pellissier and Kruger, 2011
			The value of external intelligence for strategic planning	Priporas et al., 2005
			How external intelligence is obtained and used in the strategic management process	DuToit, 2003
			The process used to create and maintain intelligence support programs in organizations	Bose, 2008
			Scanning activities and sources of strategic information	DuToit, 2016
			Intelligence collection practices based on Miles and Snow's strategy typologies	Yap et al., 2012
33	inform, data, process, use, decis, project, organis, compani	Intelligent systems as a substitute to intuitive judgement	Information source/mode impact on scanning behavior as a part of strategy process	Robinson and Simmons, 2017
			Impact of big data on board-level strategic decision-making	Merendino et al., 2018
			Data driven strategic decision-making processes replacing intuitive judgements	Constantiou et al., 2019
			The relationship between external data collection practices and strategy formulation process	Cavallo et al., 2021
			Competitive intelligence model in parallel to strategy process	Gibbons and Prescott, 1996
			A system for detecting weak signals and surveilling strategic discontinuities	Nunes and Da Silva, 2019
			Designing an intelligence system for firm appraisal as part of strategic decision making	Walters et al., 2003

Appendix 5. Most representative papers of the entanglement discourse

The entanglement discourse				
Topic	Top words	Issue	Focus	Most representative papers
1	tool, use, specifi, defi, significant, identifi, benefi, rst	A strategy & performance tool	Establishing the position of analytics techniques in the strategic-level decision support tool market	Stenfors et al., 2007
			Understanding the antecedents of big data analytics value at a firm level	Corte-real et al., 2019
			The effects of big data analytics-enabled sensing capability and analytics culture on strategic business value	Fosso wamba et al., 2020
			Examining the impact of big data on performance	Ying et al., 2021
			Improving firm performance using big data analytics capability & business strategy alignment	Akter et al., 2016
2	data, use, report, can, search, system, relev, analysi	Data architecture infusion	Designing and integrating automated archiving component into a BI system to reduce intelligence search effort	Schulz et al., 2015
			Deep link prediction and competitive intelligence analysis to uncover business trends and opportunities	Jeong et al., 2021
			Using a conceptual system for weak signals classification to detect threats and opportunities from the web	Nunes and Da Silva, 2019
			Analysis of text & web mining & visualization-based intelligence tools	Bose, 2008
			A strategic decision-making architecture for adaptively informing decisions in human-computer collaboration	Bayrak et al., 2021
4	valu, analyt, data, busi, use, manag, research, organ	Integration for value creation	Developing temporal factors to examine the value of analytics usage	Conboy et al., 2020
				Bordeleau et al., 2020

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The entanglement discourse				
Topic	Top words	Issue	Focus	Most representative papers
			Studying the conditions favoring value creation of big data analytics	
			Business analytics success model for value creation	Seddon et al., 2017
			Management challenges to address to achieve business analytics transformation and value creation	Vidgen et al., 2017
			Embedding analytics into organizations to transform information into insights, then action	LaValle et al., 2011
			Proposing a process model for data-driven strategic decision-making	Lu et al., 2020
			Developing and evaluating a prototype dashboard for the VRIO assessment of business analytics capabilities.	Rivera and Shanks, 2015
			Using analytics to innovate and gain competitive advantage	Kiron et al., 2012
			Assessing the challenges and opportunities for business analytics to generate value competitive advantage	Gillon et al., 2012
			Integrating analytics into core business functions to capitalize on insights from big data	Davenport and Barth, 2012
5	perform, capabl, bda, data, busi, analyt, studi, big	Capability modeling	Improving firm performance using big data analytics capability & business strategy alignment	Akter et al., 2016
			The effects of big data analytics-enabled sensing capability and analytics culture on strategic business value	Fosso wamba et al., 2020
			Supporting big data analytics capabilities by a good level of data quality to yield better competitive advantage	Corte-real et al., 2020
			The relationship between big data analytics technologies and innovation capabilities	Mikalef et al., 2019
			Assessing big data analytics value in several stages of the value chain	Corte-real et al., 2017
			The mediating role of data driven culture on the impact of business analytics on performance	Chaudhuri et al., 2021
			Using big data to innovate business models and handling the impact of digital transformation	Bouwman et al., 2019
			The alignment between big data analytics capability and strategy and its impact on firm performance	Gu et al., 2021
			Unpacking analytics-driven value creation capability to sustain competitive advantage	Hossain et al., 2021
			A big data analytics capability model that entangles process-oriented dynamic capabilities and firm performance	Fosso Wamba et al., 2017
			Developing a big data analytics quality model and measuring its impact on firm performance	Fosso Wamba et al., 2019
			The underlying mechanisms of organizations' big data analytics usage and its effects on value creation	Chen et al., 2015
			Exploring the impact of big data analytics capabilities on business model innovation	Ciampi et al., 2021
6	decision-mak, process, use, inform, system, research, bis, qualiti	Analytics-based strategic decision making	The role of sense-making in linking the processes of organizational knowledge and strategic decisions	Hasan and Gould, 2001
			How business intelligence system dimensions are interrelated and how they affect business intelligence use	Popovic et al., 2012
			The scanning activities of firms and their attitudes toward intelligence scanning for strategic planning	Costa and Teare, 2000
			The use and organizational facilitation of business analytics	Cao and Duan, 2017
			How information-sharing values influence the use of information systems in the BI systems context	Popovic et al., 2014
			The link between competitive advantage and business analytics and its link to strategic decision making	Cao et al., 2019
			The impact of big data analytics on firms' high value business performance	Popovič et al., 2018
			A comprehensive understanding of the intelligence scanning process & its impact on strategic change	Correia and Wilson 1997
			The impact of computerized intelligence systems on executives' strategic decision making and firm performance	Hasan and Hasan 1997
9	strategi, bsc, map, model, use, can, level, process	Cognitive aid modeling	Designing computerized cognitive aids for the strategy execution process	Singh, 1998
			Designing an intelligent strategy map using big data analytics techniques	Rezaee et al., 2021
			Big data analytics based tool for visualizing and designing strategy	Aldea et al., 2018
			The link between knowledge management, big data and business strategies	Venkitachalam and Ambrosini, 2017

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The entanglement discourse				
Topic	Top words	Issue	Focus	Most representative papers
			Extending strategy tools by designing an automated computerized SWOT analysis	Pröllochs and Feuerriegel, 2020
			Proposing a dynamic interactive framework to link business intelligence with strategy	Tu and Chang, 2007
			Defining a modeling framework for business model with strategic reasoning	Rezaee et al., 2008
10	capabl, competit, market, technolog, valu, model, resourc, product	A technology for simulations analyses	Investigating the potential of competitive intelligence utilization on strategic response capability	Heinrichs and Lim, 2008
			Examining how data resources can help organizations create and capture value	Mamonov and Triantoro, 2018
			A conceptual model to identify the sources of competitive advantages from big data analysis adaptation	Shan et al., 2018
			Identifying value creation success criteria for corporate foresight activities	Rohrbeck, 2012
			Investigating how dynamic business intelligence capabilities impact the strategic agility of BI systems	Knabke and Olbrich, 2017
			A Simulation-based strategic decision support system for innovative business development & strategic planning	Yan, 2018
11	busi, model, data, digit, develop, custom, servic, bank	Data-driven business model innovation	How predictive analytics facilitate business model innovation and transformation	Ardolino et al., 2018
			Maximizing the benefits from a business intelligence application to transform strategy	Audzeyeva and Hudson, 2016
			How big data impacts the adaptation and innovation process of business models	Liu and Bell 2019
			How to implement big data analytics to respond to disruptive technologies and change firm performance	Naimi-sadigh et al., 2021
			A deep link prediction model to discover diversifiable businesses and establish diversification strategies	Jeong et al., 2021
			Leveraging information networks and big data to innovate business models or to develop new ones	Sorescu, 2017
			How predictive analytics facilitate business model innovation and transformation	Ardolino et al., 2018
			The challenges and opportunities of data-driven business models at a strategic level	Zaki, 2019
			Examining the corporate expectations surrounding data-mining efforts and failure to probe its value	Wencer, 1998
12	measur, perform, use, system, organiz, busi, manag, organ	Measuring big data analytics success	The relationship of BI functionalities, performance measurement capabilities, & strategic momentum	Peters et al., 2018
			Examining the influence of organizational controls on strategic integration and use of BI systems	Elbashir et al., 2011
			Theorizing the importance of business intelligence systems assimilation, and the need for shared knowledge among the strategic and operational levels as the drivers of business intelligence business value	Elbashir et al., 2013
			Measuring the realized business value from BI based on a process-oriented framework	Elbashir et al., 2008
			Developing a firm-specific sensing capacity that can provide a basis for sustainable competitive advantage	Hallin et al., 2017
			Developing a model of the paths by which BI assets and BI capabilities create business value	Fink et al., 2017
			A system for retrieving balanced scorecard performance measures of companies' particular strategies	Sohn et al., 2003
			A data collection tool for scanning and strategic planning as enablers of organizational responsiveness	Hoyt et al., 2007
13	agil, technolog, swot, lean, practic, alt, factor, can	Agile data based-strategy analysis tools	Connecting big data technologies with SWOT analysis to carry out a firm's appraisal	Kangas et al., 2003
			A framework examining the relation between big data analytics knowledge and competitive advantage	Raji et al., 2021
			A hybrid method combining SWOT analysis and big data as a comprehensive strategic planning tool	Kajanus et al., 2004
			Integrating competitive intelligence into the strategy building process to achieve stronger business performance	Sahin and Bisson, 2021
			Investigating the potential of competitive intelligence utilization on strategic response capability	Heinrichs and Lim, 2008
			Big data analytics capability usage and integration with organizational readiness and design for performance	Popovic et al., 2018
14		Active decision support system	How organizations can prevent strategic surprise through the practice of competitive intelligence and foresight	Neugarten, 2006

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The entanglement discourse				
Topic	Top words	Issue	Focus	Most representative papers
	decision-mak, dss, strateg, system, use, inform, decis, data		Investigating sources of strategic failure for decision-makers using decision support and big data	Aversa et al., 2018
			The connection between strategic thinking and active decision support systems for strategic decisions	Brännback, 1997
			Developing suitably adapted business intelligence systems for executive decision-making	Ow and Morris, 2010
			The understanding of big data changes & the significance they carry for strategy making	Constantiou&Kallinikos, 2015
			Designing a decision support system to help understand the dynamics of the industry and key players	De Heer, 2003
15	strategi, chang, busi, compani, one, will, need	Strategic change & big data analytics exploitation	Challenges of intelligence scanning vis-à-vis strategic inflection point	Huffman, 2004
			Big data as a management revolution and the success stories of big data transition	Mcafee and Brynjolfsson, 2012
			Refocusing intelligence to produce critical strategy inputs	Fahey, 2007
			New filtering and indexing technologies to step up the process of scanning for strategic management	Myers, 1999
			Fully exploiting data and analytics through mutually supportive capabilities	Barton and Court, 2012
			Proactive scanning and use of formal strategic planning to anticipate change and better perform	Smith, 1998
18	strategi, compani, effect, use, factor, manag, studi, organ	Big data analytics compliance	The relationship between intelligence scanning and the characteristics of the organization and its environment	Kourteli, 2005
			Using BI technologies and its impact on strategy execution, process efficiency, and fact-based decision-making	Yeoh et al., 2014
			Intelligence collection practices based on Miles and Snow's strategy typologies (defender, analyzer, prospector)	Yap et al., 2012
			Investigating the support of executive information system for the phases of the strategic management process	Singh et al., 2002
			Developing suitably adapted business intelligence systems for executive decision-making	Ow and Morris, 2010
			The impact of BI on organizational strategy, structure, and organizational effectiveness	Arefin et al., 2015
20	busi, model, process, queri, use, can, design, goal	Modeling strategic mapping and action	Enabling BI systems to convert data into strategic intelligence through query-based process analytics	Polyvyanyy et al., 2017
			A strategic modeling framework to help understand the rationale behind strategic actions	Samavi et al., 2009
			A multi-perspective modeling approach that involves supporting strategic decision-making through simulations	Fayoumi & Loucopoulos,2016
			A business analytics success model that contributes to business value	Seddon et al., 2017
			Fully exploiting data and analytics through mutually supportive capabilities	Barton and Court, 2012
			Prescriptive and predictive analytics to generate strategic map and strategic action plans	Wang et al., 2018
21	integr, evalu, agent, system, data, user, need	Integrating analytics with management systems	Integrating big-data ERP with business analytics to gain sustainable competitive advantage	Shi and Wang, 2018
			Developing an automated system for business intelligence to better fit business and users' needs	Brichni et al., 2017
			An intelligent software agent that helps in accomplishing scanning activities for executives	Liu, 1998 c
			A software agent approach to offer active scanning support to managers	Liu, 1998 b
			How executive information systems technology can respond to dynamic business conditions	Volonino et al., 1995
26	valu, capabl, process, data, big, analyt, busi, research	Value-based analytics investment	Exploring the value creation capabilities of big data through strategic alignment	Brinch et al., 2020
			Prescriptive and predictive analytics to generate strategic map and strategic action plans	Wang et al., 2018
			Identifying firm-level capabilities required to create value from big data	Brinch et al., 2021
			Examining the impact of big data management on organizational performance	Ying et al., 2021
			Proposing big data strategy as a new basis for competitive advantage for business model innovation	Opresnik and Taisch, 2015
			Presenting a framework outlining the multiple value directions big data can generate	Elia et al., 2019
				Gupta and George 2016

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The entanglement discourse				
Topic	Top words	Issue	Focus	Most representative papers
			Building a big data analytics capability and testing its relationship with firm performance	
			The concept of big data capability and its relationship to strategic orientation and organizational culture	Lin and Kunnathur 2019
			The traditional links between enterprise strategy, structure and how big data is affecting this dynamic	Bhimani, 2015
			How big data is being used in practice to craft strategy and the company business model	Woerner and Wixom 2015
			The potential factors that can influence the effective use of big data	Surbakti et al., 2020
			How big data improves functional capabilities within organizations & shapes entirely new industries	Mazzei and Noble 2017
31	project, busi, data, analyt, big, studi, differ, research	Project-based routinization of analytics	How big data entails a radical reconfiguration of strategic management tools and the capitalist view of the firm	Roth et al., 2019
			Leveraging big data analytics to build dynamic capabilities and support strategic objectives	Mikalef et al., 2021
			The analytical process of business analytics sensemaking and influence of strategy and business model	Zamani et al., 2021
			The gradual routinization of big data and business analytics into organizational operations to generate value	Mikalef et al., 2020
			The relationship between big data analytics technologies and innovation capabilities	Mikalef et al., 2019
			Big data analytics capability usage and integration with organizational readiness and design	Popovic et al., 2018
32	strateg, strategi, manag, plan, process, analysi, system, chang	Aligning analytics with strategic objectives	Integrated decision support for strategic planning	Tuncikiene et al., 2010
			Integrating big data in the process of strategic management	Viitanen and Pirttimaki, 2006
			Proposing a dynamic interactive framework to link business intelligence with strategy	Tu and Chang, 2007
			Integrating big data analytics with strategy tools to support strategy processes	Kunc & O'brien, 2018
			A framework for aligning BI with corporate strategy	Dokhanchi and Nazemi, 2015
			Incorporating analytics with portfolio matrices to help evaluate and form strategic plans	Chien et al., 1999
34	map, model, use, support, system, inform, organis, causal	Modeling human & organizational knowing	Group decision support for the firm's core capabilities	Lin and Hsu, 2007
			Cognitive decision models for aiding the formulation and analysis of strategic problems	Druckenmiller and Acar, 2009
			Establishing a link between weak signals, BI, and business strategy	Rouibah and Ould-Ali, 2002
			Understanding the role of BI in organizational knowing	Shollo and Galliers, 2016
			Designing decision support system for specific competitive strategy	Cook et al., 1998
			Operationalizing latent constructs of the strategy map using big data analytics techniques	Castellano and Del Gobbo, 2018
			Determining firm's core capabilities via soft computing algorithms and decision support system	Lin et al., 2013
			Using big data analytics technology to develop an intellectual balanced score card knowledge-based system	Huang 2009
			Designing a hybrid approach based on human judgment & big data for formulating strategies	Li and Li 2009

Appendix 6. Coding strategies for deconstructive discourse analysis (Based on Beath and Orlikowski (1994, p. 356) and Martin (1990, p. 355))

Coding strategies	**The input-output discourse**	**The entanglement discourse**
Dismantling a dichotomy, exposing it as a false distinction	The text holds these dichotomies as mutually exclusive, although they are false distinctions. The single determinant argument vs the equifinal argument: Big data as an imperative and only decisive factor for organizational structure. In contrast, organizational size, hierarchy, and routines are the only decisive factors in shaping structure. Automated processes vs human strategist:	These dichotomies imply three orthogonal couplets that cannot exist simultaneously. The symmetric argument vs. the asymmetric argument: The text imposes uniformity between strategy actors and big data analytics as equivalent agents in the coming through of the social practice of strategy. The text, however, adopts Cartesian dualism between (knowers) strategy actors and (object to know) big data analytics, which contradicts the text's uniformity

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Coding strategies	The input-output discourse	The entanglement discourse
	The dichotomy between automated processes and human strategist is rooted in the premise of natural selection that enrolls both parties in a survival of the fittest rather than an involvement in simultaneous usage and mediation. Powerful vs non-powerful actors: The dichotomy between powerful executives and non-powerful actors results from a top-bottom approach that, if dismantled, the dichotomy withers. Big data analytics output vs executives intuitive judgments: The premise of the first statement is that the intrusion of big data analytics in executives' decisions results from its relevant output. However, this position seems doctrinal when executives' intuitive judgements trump this same output because of the difficulty in modeling contextual acumen.	premise that supposedly rejects the 'material/human' distinction in favor of their entanglement. The Analytical culture vs. deep structure: Structure follows analytical culture and helps diffuse it. Analytical culture fosters ambidexterity across organizational layers. The Data savvy vs non-data savvy: Data savvy scientists do not replace non-data savvy actors in strategizing work, but each participates in the activities that help create and capture value. Therefore, the two contrasts are fallacious.
Attending to disruptions & contradictions in the text, i.e., places where the text fails to make sense	The following passages are silent about what allows or makes "… Big data analytics [become] a new enabler of competitive advantage …" (Wamba et al., 2017, p. 357). The 'means' whereby big data analytics unleash competitive advantage is excluded and therefore the text fails to make the sense it seeks to convey.	The meaning this statement attempts to deliver is to advise against "… The lack of alignment … between the Organization's existing culture … and BDA capabilities … [because it] can erode a firm's performance …"(Côrte-Real et al., 2019, p. 167). However, the 'cause' is omitted, which yields a disruption in meaning.
Scrutinizing naturalness claims or arguments which depend on something other than logical consistency or empirical evidence	Who makes the claim that "… BDA is … a game changer"? (Wamba et al., 2017, p.357) and based on what Characteristics and mechanisms it attained such a status? The claim here is based on consultancy hype rather than empirical evidence.	The argument that "… data scientists have the sexiest job of the 21st century …" (Fosso Wamba et al., 2019, p. 527) depends on a subjective enthusiasm or judgment rather than logical consistency.
Examining silences, i.e., examining what is not said	The text is silent about: Why automated processes should replace human decision-making, although evidence shows that in dynamic environments intuitive judgements rooted in contextual knowledge supersedes big data analytics.	The text is silent about personal characteristics, routines, and the nitty-gritty doings of non-savvy strategists, which define the nature of their strategizing activities.
Focusing on the element that is most marginalized in a text or a context	"… and [other] challenges BD brings …" (Merendino et al., 2018, p. 74). Other in this statement indicates all those challenges that the text note and yet marginalizes from the discussion.	(… integration with [other] systems …" (Işik et al., 2013, p. 21). The reader cannot know more about these other systems to be integrated with BI because the text treats them as insignificant.
Interpreting metaphors as a rich source of multiple meanings	The word "… keystone …" (Elia et al., 2019, p. 11) indicates that big data analytics is an irreplaceable element, a cornerstone that changes the nature of strategizing and holds its activities together and dictates who does what. Keystone also implies that big data is the summit of strategizing work that allows to bring new insights that may replace human judgement.	The word "… staff …" (Conboy et al., 2020, p. 10) in reference to non-savvy data strategists as opposed to the word "… practitioner …." (Conboy et al., 2020, p. 10) to describe data-savvy actors suggests a fundamental shift from viewing non-data savvy as 'actors' that are actively engaged in strategizing activities to becoming a group of employees that assist the data- savvy ones. Both words also recall a hierarchical structure (hospital, military, etc) where the practitioner adheres to the core profession, and the staff is in charge of the day-to-day tasks.
Analyzing double-entendres that may point to an unconscious subtext	The phrase "… black box …" (Pryor et al., 2019, p. 1979) compares executives' cognitive behavior and decision making to an opaque and complex equipment with mysterious intuitions that are complicated to model and quantify.	The phrase "classical house …" (Audzeyeva and Hudson, 2015, p. 4) compares the organizational structure to that of a house which reflects the style of a closed and deeply connected architecture that can be challenging to renovate and may cause inertia if its ingrained systems conflict with the new analytical culture.

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Zuboff, S., 1988. In the Age of the Smart Machine. Basic Books, New York.

Yassine is a Post-doctoral Researcher of strategy at the University of Vasa. His research interest focuses on the intrusion of technology in management and organization studies (MOS) and organization theory (OT).

Marko is a Professor of Strategy at the University of Vaasa, and a visiting professor at the University of South-Eastern Norway, USN Business School and Luleå University of Technology. Kohtamäki takes special interest in strategic practices, strategic agility, and business intelligence. Kohtamäki has published in distinguished international journals such as Strategic Management Journal, International Journal of Operations and Production Management, Industrial Marketing Management, Long Range Planning, Strategic Entrepreneurship Journal, International Journal of Production Economics, Technovation, Journal of Business Research, amongst others.

Mikko is an assistant professor of accounting at the University of Vaasa, where his current position focuses on data analytics and its impact on accounting and finance research. He has over fifteen years of research experience in multiple disciplines like astronomy, statistics, computer science, finance and accounting. His research interests include natural language processing, big data analytics, deep learning, ensemble methods, explainable artificial intelligence and their applications in business disciplines.

Sotirios is Professor of Strategic Management and head of the Strategy and International Business (SIB) group at the Warwick Business School (WBS) UK. His research interests lie at the intersections of strategy practices and processes in complex organizational settings. He is interested in the discursive, cognitive and visual activities organizational actors employ to foster strategic agility.