Sensemaking and Sustainability: A Sensemaking Perspective on the Ethical Use of Big Data in Marketing Strategizing

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Abstract Despite the ethical concerns over the datafication and surveillance of individuals and groups, companies are making ever greater investments in big data. The assumptions underpinning this movement are: (1) organizations are passive implementers of big data—more data is the inevitable consequence of technology and a competitive necessity for business, (2) more data offers a more objective and accurate picture of reality and (3) more data enables better prediction. We argue that this perspective is strategically unsustainable and abdicates ethical responsibility.

In this chapter, we adopt a sensemaking perspective (Weick in (1995) Sensemaking in organizations (Vol. 3). Sage) to challenge each of the assumptions of inevitability, objectivity, and predictability. Building on this critique, we discuss the role that organizations can play in creating alternative sustainable futures with big data and explore the legal and ethical consequences of their actions. In addition, we advocate that, from a sensemaking perspective, organizations can use big data to cultivate sustainable learning and innovating communities of both employees and customers.

Keywords Big Data · Sensemaking · Sustainability · Strategizing · Organization

> We put so much investment in being saved by these objects we create, by these technologies. But our real resource is ourselves, our communities, our relationships, our stories and our narratives.

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W. Leal Filho and V. Kuzmanović (eds.), *Sustainable Development Seen Through the Lenses of Ethnoeconomics and the Circular Economy*,
https://doi.org/10.1007/978-3-031-72676-7_7

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1 Introduction

"The technology that connects us also divides us, manipulates us, polarize us, distract us, monetize us and controls us" (Orlowski & Rhodes, 2020). A Netflix documentary *The Social Dilemma* went viral in September, 2020 in the middle of the COVID pandemic. The film highlighted our shared social dilemma (i.e., mental health dilemma, the democracy dilemma, and the discrimination dilemma) caused by social media and the forces controlling these online platforms (i.e. companies, politicians and other interested parties). It features technologists, researchers and activists working to align technology with the interests of humanity, who raised their concerns over the datafication and surveillance of citizens.

Big data is a term for the exponential explosion in the volume, variety and velocity of data we see today. The world now generates an estimated 2.5 quintillion bytes of data every day, (Rayaprolu, 2023). It comes in three forms: (1) Structured data which and exists in predefined formats like credit card numbers and GPS coordinates; (2) Unstructured data such as social media posts and blogs; and (3) Semi-structured data which is a mix of structured and unstructured data such as email addresses. Despite the concerns over the datafication and surveillance of citizens, companies have invested billions of dollars into the harvesting and storage of data (Brown, 2021). This drive is rooted in the belief that data can capture social life in an objective format (Hintz et al., 2018). Big data's ascendance rests on two promises. First, that more data offers a more objective and accurate picture of reality, which can be leveraged for competitive advantage (e.g., Mayer-Schönberger & Cukier, 2013; Rust & Huang, 2014). Second, that "using big data leads to better predictions and better predictions yield better decisions" (McAfee et al., 2012, p. 64). This 'dataism' view of big data, promoted by big tech and consultants, argues for a new era of empiricism, where data, combined with analysis can reveal intrinsic truths, independent of theoretical perspective (Kitchin, 2021).

We argue that mangers have brought into a view of big data that is strategically unsustainable and abdicates ethical responsibility. Moreover, this view marginalizes the negative impacts of Big Data on individuals, organizations, and society. Is there an alternative framing of Big Data that allows for an ethical and sustainable future?

We suggest that Weick's (1995) theory of sensemaking can provide such a framing. Sensemaking involves "placing stimuli into some kind of framework to comprehend, understand, explain, attribute, extrapolate and predict" (Starbuck & Milliken 1988, p. 51). It is seen as a key managerial and leadership ability that enables firms to cope with, and act in, the rapidly changing and complex environments (Ancona, 2012; Becke, 2013).

The rest of the chapter is structured as follows. We start by reviewing the tension in current views of big data. After that, we explore the relationship between sustainability and ethical use of big data. Thirdly, we examine the assumptions underpinning the unsustainable view of big data, and then we introduce a sensemaking perspective. Next, we explore the role that big data can play from a sensemaking perspective. Finally, we draw on this more nuanced framing of big data to discuss the role that organizations can play in creating ethical and sustainable futures.

2 The Tension in Current Views of Big Data

Over past one decade or so, big data has been generating excitement amongst both practitioners and academics. Advocates of big data (e.g., Chen et al., 2012, Constantiou & Kallinikos, 2015, Davenport et al., 2012, LaValle et al., 2011, Mayer-Schönberger & Cukier, 2013, McAfee et al., 2012, Rust & Huang, 2014, Varian, 2010, 2014, Woerner & Wixom, 2015), contend that big data is a revolution that will transform how we live, giving companies a competitive advantage by enabling them to assess, analyze and respond to environmental trends, and offer new types of service. Advocates argue that big data can provide a new era of empiricism where data can 'speak for itself' without theoretical framing of interpretation (Kitchin, 2021). For example, Anderson (2008), former Editor-in-Chief at Wired magazine, contends that "the data deluge makes the scientific method obsolete." Echoing this, Prensky (2009) argues that correlation is enough and we can stop looking for theoretical causal models.

An example was cited in Kitchin (2021)'s work from retail to illustrate this perspective. A retail chain analyzed 12 years of purchase transactions. By discovering correlations between certain items, new product placements and shelf space management were altered, resulting in a 16% increase in revenue per shopping cart in the first month. A hypothesis was not developed or tested to explain why product A was often bought with product B. The data were simply queried to identify correlations that existed. Siegel (2013, p.90) argues, "We … don't necessarily care (about causation) … the objective is to predict …(not) … understand the world…". As a result, managers know without understanding: the "what" trumps the "why". From this perspective, big data is touted as "a source of new economic value and innovation" (Mayer-Schönberger & Cukier, 2013, p.12, Chen et al., 2012).

However, there are dissenting voices (e.g., Crawford et al., 2014, Crawford, 2014, Naimi & Westreich, 2014, Markus, 2015, Newell & Marabelli, 2015, Richards & King, 2013, 2014, Zuboff, 2015, O'neil, 2017), who critique the hype around big data, and point out the threats big data brings to people's identity, privacy, security, and economic wellbeing. Richards and King (2013) highlights three paradoxes in the rhetoric about big data: the transparency paradox, the identity paradox and the power paradox. Zuboff (2015) argues that we live in an era of 'surveillance capitalism'. While Crawford et al. (2014) argue that the promise of big data as a predictor of social behavior ignores a key insight from sociology: aggregated, individual actions

cannot, explain the emergent dynamics of social interaction. O'neil (2017) points out the flaws in big data models:

> many of these models encoded human prejudice, misunderstanding, and bias into the software systems that increasingly managed our lives. Like gods, these mathematical models were opaque, their working invisible to all but the highest priests in their domain: mathematicians and computer scientists. Their verdicts, even when wrong or harmful, were beyond dispute or appeal. And they tended to punish the poor and the oppressed in our society while making the rich richer. (p. 3)

These dissenting voices collectively highlight the manifest flaws in the mainstream perspective on big data. Next, we examine the relationship between sustainability and ethical use of big data.

3 Sustainability and Ethical Use of Big Data

Sustainability involves making decisions that benefit the society, environment, and economy at the same time, rather than trading-off one against the others (Willard & Hitchcock, 2015). The relationship between sustainability and the ethical use of big data presents a complex and multifaceted issue, as it embodies a tension within the current views of big data. This issue can be analyzed from two complementary perspectives: the enablers' side and the barriers' side.

From the enablers' side, big data can facilitate responsible business management, echoing the paradigm shift in the circular economy, altering purchase behavior from ownership to service offerings (Salminen et al., 2017). Big data-enabled digital transformation allows enterprises to capitalize on new business and optimization opportunities using technologies such as cloud, mobile, and social networks with increasing intelligence and automation (Feroz et al., 2021). Digital transformation of supply chain management increases efficiency within the supply network. Furthermore, big data can bridge the gap between supply chain and consumer analytics. Sustainability has emerged as a prevailing marketing and branding strategy, providing companies with a competitive advantage by aligning their values with younger generations' preferences. The increasing accessibility of big data has played a vital role in facilitating this shift towards sustainability practices (Raut et al., 2019). By integrating sustainability practices into their operations and supply chain management, companies can enhance their brand image, appeal to sustainability-conscious consumers, and leverage insights from big data analytics to inform marketing and branding strategies. Companies can use big data to gain insights into consumer preferences and behavior related to sustainability, tailoring their messaging and experiences accordingly to make their sustainability initiatives more effective (Kitchens et al., 2018).

The underexplored aspect of big data lies in the challenges and barriers it presents. As with any technology, the large-scale use of big data will inevitably have some undesirable consequences—both foreseeable and unpredictable. It is crucial to begin exploring the potential unwanted repercussions of the big data revolution, notable, the

unique challenges and requirements of warehouse-scale data centers, i.e., large-scale computer systems designed for processing and analyzing massive amounts of data (Schadt et al., 2010). In fact, data centers are the factories of the twenty-first century which consume a tremendous amount of energy (Willard & Hitchcock, 2015). While in technical parlance the "Cloud" might refer to the pooling of computing resources over a network, it has come to signify and encompass the entire gamut of infrastructures that make online activity possible, including services such as Instagram, Hulu, and Google Drive, etc. Monserrate (2022)'s research sketches some of the particular ways that cloud computation contributes to climate change and the Anthropocene. Particularly, this research reveals various material and ecological impacts of computation and digital data storage practices and pinpoints the environmental toll of digital life and the complexity of infrastructures involved in its operation. Thus, the Cloud is not only material, but also ecological in embodiment and effect. As the Cloud expands, its negative impacts on environment increases, despite the best efforts of engineers, technicians, and executives to balance profitability with sustainability. Indeed, the Cloud now has a greater carbon footprint than the airline industry. A single data center can consume the equivalent electricity of 50,000 homes.

Monserrate (2022) further reveals that some of the "hyper-scale" data centers, such as those owned by Google, Facebook, and Amazon, have committed to carbon offsetting, and investing in renewable energy such as wind and solar. However, many smaller data centers lack the resources to pursue sustainability initiatives, and they are often located in old buildings that are not optimized for the ever-changing power, cooling, and data storage needs. Many companies, universities, and others who operate small-scale data centers have begun to transfer their data to hyper-scalers or cloud colocation facilities to cut energy costs.

According to Sattiraju (2020), Google's parent company, Alphabet, is building more data centers across the U.S. to power online searches, web advertising and cloud services. The company has boasted for years that these huge computer-filled warehouses are energy efficient and environmentally friendly. However, there's a cost that the company tries to keep secret. These facilities use billions of gallons of water, often in dry areas with limited water resources. This shift from cooling air to cooling water is an attempt for those data centers to reduce carbon footprint, but it comes at a cost. For example, residents of Bluffdale, Utah, suffer water shortages and power outages due to the nearby Utah Data Center, a facility of the U.S. National Security Agency (NSA) that guzzles seven million gallons of water daily to operate (Monserrate, 2022).

What is worse is that, since customers expect their data and cloud services to be available anywhere, anytime, data centers are designed to be redundant, ensuring that if one system fails, another can take over at a moment's notice, preventing service disruptions. Therefore, data centers require a great deal of energy beyond cooling. It is estimated that only 6–12 percent of computational energy is consumed by active computational processes, and the rest is used for cooling and ensuring redundant fail-safe chains are in place to avoid costly downtime (Monserrate, 2022).

Despite efforts to mitigate the environmental harms of big data, such as carbon emissions, water consumption, noise, and toxic e-waste, there is a vicious cycle

where the increasing demand for big data further exacerbates these harmful effects. To complicate matters, managers offload the environmental costs associated with the storage and processing of big data to third parties (such as Amazon's AWS), thus abdicating ethical responsibility. To break this vicious cycle, we need to reexamine the dominant framing of big data. We argue that adopting a sense-making approach can help promote a more sustainable and responsible approach. This approach involves creating, interpreting, and enacting responsible and ethical practices to leverage the full potential of big data for the greater good while minimizing harm to the society, environment, and vulnerable populations.

4 Assumptions Underpinning the Dominant View of Big Data

There is a powerful and attractive set of ideas underpinning the current framing, i.e., the dominant view of big data: inevitability, objectivity, and prediction trumps explanation.

First, organizations are passive implementers of big data—more data is the inevitable consequence of technology and a competitive necessity for business: adopt big data or die (e.g., Mayer-Schönberger & Cukier, 2013; Woerner & Wixom, 2015). In reviewing statement from a White House report on big data (White House, 2014) and a 2009 interview with Google Chairperson Eric Shmidt (Newman, 2009), Zuboff (2015) finds that, "big data is cast as the inevitable consequences of a technological juggernaut with a life of its own entirely outside the social. We are but bystanders" (p. 75).

Second, more data offers a more objective and accurate picture of reality. Here embedded another assumption that, the environment, consists of customers, competitors, markets, advanced technologies, and so on, exists in an objective reality that data reflects (boyd & Crawford, 2012; Crawford et al., 2014). Puschmann and Burgess (2014) reveal the dominant metaphors used in the rhetoric around big data. First, it is "a *resource* to be consumed". Second, it is "a natural *force* to be controlled." They conclude that these metaphors encourage the view that big data as value-neutral resource and an objective force. Indeed, "the rhetoric of objectivity can be very seductive to public policy makers traversing the complex world of social phenomena" (Crawford et al., 2014, p. 1667)".

To compound matters, some data analytics software is sold on the misleading notion that relationships within big data are inherently truthful, and that meaning transcends context or domain-specific knowledge (Kitchin, 2021). For example, the data mining and visualization software Ayasdi claims to be able to "automatically discover insights -- regardless of complexity -- without asking questions." Ayasdi's customers can finally learn the answers to questions that they didn't know to ask in the first place. It further claims to have eliminated the human element of data mining, as well as all the bias that comes with it (Kitchin, 2021).

The third assumption is that prediction trumps explanation. Big data doesn't aim to explain the world, just predict what will happen; correlation patterns are more important than causal relations (Siegel, 2013). More data means greater predictability of customers and markets. "Using big data leads to better predictions and better predictions yield better decisions" (McAfee et al., 2012, p. 64).

Next, we re-examine these assumptions from a sensemaking perspective (Weick, 1995). We discuss how sensemaking works in decision making and then reinterpret big data and the role that organizations play in its use from a sensemaking perspective.

5 Sensemaking and Strategizing

Strategy is not something that an organization *has* but something its members *do* (Johnson et al., 2003) and the strategy-as-practice approach speaks of "strategizing" as the "doing of strategy" (Jarzabkowski, 2004; Whittington, 2006). Indeed, from a sensemaking (Weick, 1995) perspective, strategizing is seen as an ongoing process involving organizational participants' constructing and reconstructing their views of the past, present and future (Kaplan & Orlikowski, 2013). In other words, the process of making strategic decisions is an ongoing, social activity that involves negotiations, discussions, and situated practices that strategists use to accomplish their goals (Jarzabkowski et al., 2007; Kaplan & Orlikowski, 2013).

Organizations begin new strategizing when an existing strategy is disrupted (e.g., a marketing problem or opportunity is detected). Strategists then try to get rid of the 'disordered' situations through creating 'new' orders and making events rationally accountable (Weick, 1995). They get together to exchange ideas about what happened in the past, what is currently at stake now and what is coming up in the future (Kaplan & Orlikowski, 2013). In other words, they used 'sensemaking' to guide them toward identifying substitute actions (Weick et al., 2005) to resolve marketing problems or leverage marketing opportunities.

As previously mentioned, sensemaking means putting stimuli into a framework to comprehend, understand, explain, attribute, extrapolate, and predict things (Starbuck & Milliken, 1988). It consists of three basic components: (1) cues, (2) frames, and (3) the linking of cues and frames (Weick, 1995). "'Cues' are information from current environments and trigger a drive to make sense of the situation. 'Frames' are knowledge or mental structures that include rules and values and serve as a guide to understanding. When people create a relation between frames and cues, they create meaning" (Miles, 2012, p. 242).

Specifically, after strategic decision-makers capture cues from the external or internal environment, they then create ways of comprehending the meaning of the event and fit these cues into their mental frames of understanding (Gioia, 1986; Taylor & Crocker, 1981). While they are translating events and developing a shared understanding among themselves, new constructs are introduced into the collective cognitive map of the organization (Daft & Weick, 1984). They then put these theories or maps into practice, a process that constitutes organizational learning (Argyris &

Schon, 1978; Hedberg, 1981). Taking action is critical because it helps decision-makers and other organization members stay in touch with the changing business environment. Rounds of sensemaking make strategizing an ongoing process. As such, sensemaking essentially serves as a springboard to action (Weick et al., 2005, p. 409) in strategic decision-making.

Next, we consider big data from a sensemaking perspective and contrast this with the dominant view of big data.

6 How Does a Sensemaking Perspective of Big Data Differ?

Recall that the dominant view of big data is underpinned by three assumptions, namely: (1) organizations are passive implementers of big data—more data is the inevitable consequence of technology and a competitive necessity for business, (2) more data offers a more objective and accurate picture of reality and (3) more data enables better prediction. How does a sensemaking perspective differ from this view?

6.1 Big Data Represents an Enactment Rather Than an Objective Picture of Reality

The sensemaking perspective is grounded in two postulates: reality is perspectival and enacted.

First, effective strategizing does not require nor produce an absolute reality; it fundamentally *perspectival*. "Sensemaking is not about truth and getting it right" (Weick et al., 2005, p. 415). In a sensemaking process 'reality' is an ongoing accomplishment that emerges from efforts to create order and make retrospective sense of what occurs (Weick, 1993). Winograd and Flores (1986) describe situations of '*thrownness*', in which "people find themselves *thrown* into ongoing situations and have to make do if they want to make sense of what is happening" (cited in Weick, 1995, pp. 43–44). One of the properties of this thrownness is that strategic decision makers do not have a static representation of a situation. Patterns may be evident in retrospect, but strategists always have to deal with whatever comes up, as it comes up. The process of change is arbitrarily chopped into events. The extracted cures are then organized into a host of different patterns or possibly no pattern at all (Weick, 1995). Objective analysis (or an a-perspectival view) of a situation is impossible because "each representation is an interpretation and there is no way to settle that any interpretation is right or wrong" (Winograd & Flores, 1986, cited in Weick, 1995, p. 44).

Second, reality is enacted rather than discovered (Weick, 1995). This enactment process involves two steps. First, preconceptions are used to set aside portions of the field of experience for further attention, i.e., perception is focused on predetermined

stimuli. Second, people act within the context of these portions of experience guided by preconceptions in such a way as to reinforce these preconceptions. Hence, attention to certain stimuli will guide subsequent action so that those stimuli are confirmed as important. This is in stark contrast to the dominant view of big data, which argues that data provides a theory free, objective and unbiased view of reality. This claim is easy to dismiss, as systems are a *priori* designed to capture certain kinds of data and analytics. Such work is guided by an agenda as to what outcomes (e.g., increasing profit or market share) are being sought. Thus, identifying patterns within datasets doesn't happen in a vacuum, but is dictated by what managers deem important and previous research (Kitchin, 2021).

Etymologically, the word data is derived from the Latin *dare*, meaning 'to give' in the sense of a *fact* given as the input into a calculation. This highlight that facts are tantamount to assumptions, and that facts are taken or created from an infinitely complex environment (Kitchin, 2021). We extract elements (data, facts) through observation, computation, experiments and record keeping from an infinite world of possibilities. Thus, data are inherently partial, selective and representative. In fact, from a sensemaking perspective, data are both social and material. They do not merely represent the world but actively produce it. Big data is always used to actively intervene and change the world by its users.

Moreover, the process of interpreting data is always subject to a methodological frame. The meaning of data is inevitably based on context, motives, expectations, and actions of managers (Dourish & Gómez Cruz, 2018). When decision makers interpret big data, what they find depends on the instruments of data collection (sensors), the analytical tools and the questions they ask (methods). Not only the information (cues) that they extract from the present situations, but also their knowledge structures (frames) they acquire from their past experiences, are shaped by the instruments, sensors or tools they use. Their own values and desires influence their choices, therefore, models they build are opinions embedded in mathematics, and, despite the models' reputation for impartiality, reflect goals and ideology. After all, a key component of every model is its definition of success, i.e., what the model builder is trying to accomplish (O'neil, 2017). Patterns found within a data set are not inherently meaningful. There can be random correlations between variables and patterns within a data set, which have little or no causal significance, and they can result in serious ecological fallacies if interpreted that way (Kitchin, 2021).

In short, from a sensemaking perspective, big data represents an enactment of reality rather than an objective picture of reality. Data collection and processing is never removed from human design and bias (Crawford, 2013, O'neil, 2017). Therefore, "having the right data is usually better than having more data." (Borgman, 2015, p.2).

6.2 Organizations Are Not Passive in Their Adoption or Use of Big Data

The concept of *enactment* in the sensemaking perspective reminds us that "there is *not* some kind of monolithic, singular, fixed environment that exists detached from and external to the people" (Weick, 1995, p. 31). Rather, as part of the environment, people "act and create the materials that become the constraints and opportunities they face" (p. 31). From this perspective, big data is not an independent 'force of nature,' rather it is actively created by organizations, big and small: managers all too often forget this.

Another characteristic of sensemaking is that it begins with people, thus is grounded in identity construction (Weick, 1995). Specifically speaking, "Once I know who I am then I know what is out there. But the direction of causality flows just as often from the situation to a definition of self as it does the other way." (Weick, 1995, p. 20). What the environment or situation means is defined by who the sense maker becomes while dealing with it or what and who he represents (Weick, 1995). Thus, what big data means to us, is a function of the stories we tell ourselves about ourselves. The fact that sensemaking is self-referential suggests that self might be the text in need of interpretation, rather than the environment (Weick, 1995).

When we talk about our identities, we assume that identity originates from free choice: simply, we chose who we are (Richards & King, 2013). Yet critically, we have to be mindful of how our identity is *shaped* rather than *chosen* in the big data era. In his article, *How Netflix Is Turning Viewers into Puppets*, Andrew Leonard (2013) explains that "the companies that figure out how to generate intelligence from that data will know more about us than we know ourselves, and will be able to craft techniques that push us toward where they want us to go, rather than where we would go by ourselves if left to our own devices." Netflix uses big data shape users choices for greater profit, with little concern for the freedom or wellbeing of its viewers.

In *Social Physics*, Pentland (2014) outlines a vision to gather "the digital bread crumbs we all leave behind as we move through the world—call records, credit card transactions, and GPS location fixes" (p. 16) to predict people's behavior. In his view, big data can be used to avoid market crashes, ethnic violence, political stalemates, widespread corruption, and dangerous concentrations of power. However, to the individuals who are being tracked, such monitoring may be unacceptable, creepy, and ultimately stigmatizing (Markus, 2015): being labeled as a part of 'target' marketing, individuals are liable to discrimination (in housing, education, finance, or insurance) (Markus, 2015; Newell & Marabelli, 2015; Richards & King, 2013). Increasingly, people's choices and identity will be imposed by data processing organizations.

In all these accounts, from a sensemaking perspective, organizations are active creators of big data. Simply, big data is not "the inevitable consequence of a technological juggernaut with a life of its own entirely outside the social (world)" (Zuboff, 2015, p. 75).

6.3 *Strategizing is Driven by Plausibility Rather Than Accuracy*

From a sensemaking perspective, effective strategizing is driven by plausibility rather than accuracy (Weick, 1995). People typically think they are looking for something accurate because pursuing accuracy can sustain motivation (Weick et al., 2005). In fact, in strategic decision-making, "one thing an intelligent executive does not need is totally accurate perception" (Starbuck & Milliken, 1988, p. 40). This highlight another fallacy in the dominant view of big data era, namely that local accuracy and prediction trumps systemic understanding of the world.

In contrast, from sensemaking perspective, plausible reasoning is considered more important than accuracy of perception in managerial thinking. In plausible thinking, cogent ideas or understandings go beyond the directly observable (Isenberg, 1986). Plausible reasoning is not necessarily correct, but it fits the facts, though imperfectly at times. Moreover, it is based on incomplete information (Isenberg, 1986). Indeed, managers may benefit from inaccurate perception under certain conditions if they are able to overcome inertial tendencies and pursue goals that seem insurmountable when viewed 'objectively' (Sutcliffe, 1994). Consider Elon Musk's achievements with electric cars, dismissed at the outset by the entire auto industry.

As Weick (1995) puts it "what is necessary in sensemaking is a good story" rather than an accurate set of facts. In data-driven strategic decision making, although big data may claim to be exhaustive, it's still only a sample, influenced by the technology, platform, data ontology, and regulatory environment (Kitchin, 2021). Moreover, given a set of data, strategists will enact a variety of realities and struggle with competing interpretations of what had happened in the past, what is going on right now and what will be coming up in the future (Kaplan & Orlikowski, 2013). Managers have to developed plausible narratives rather than accurate views of the future to guide an organization in the face of uncertainty (Schryer, 1993). Thus, it is not whether big data can reveal a more accurate picture of consumers or markets, but whether the data is 'right' for strategists to produce 'actionable' intelligence that matters.

Of course, whether data is the 'right' data and whether the intelligence is 'actionable' are not determined by big data, but by the enactment of the reality of their users. As previously discussed, managers' preconceptions shape the nature of the strategic problems that they seek to address and the variables they consider important in their search for answers. As a result, an enacted environment is produced, which comprises 'real' objects -- such as marketing research questions and dataset, etc. These objects, however, are meaningless unless they are acted upon, since their meaning and content will vary. This enacted environment is "a map of if–then assertions in which actions are related outcomes" (Weick, 1988, p. 307) that in turn serve as expectations for future action and focus perception in such a way that these preconceived relationships will be supported.

The stories that managers tell about data, are more important than generating more data in the elusive pursuit of a more accurate picture of a changing reality: stories

guide and motive – data does not (Weick, 1995). Indeed, even a mythical 'complete set of data' will not necessarily mean better stories to drive strategy. In fact, too much data can hinder strategists' productivity and decision-making by providing incidental findings that are confusing and misleading (Nease, 2016).

Advocates claim that that big data is truthful, and that meaning transcends context (Kitchin, 2021), this is impossible from a sensemaking perspective. This is because context is an 'ongoing situation' into which strategists are thrown and from which they have to extract the 'cues' (Weick, 1995; Winograd & Flores, 1986). The knowledge or mental structures that include rules and values must serve as the 'frame' in a sensemaking process to guide understanding (Gioia, 1986; Taylor & Crocker, 1981).

In conclusion, from a sensemaking perspective, effective strategizing is driven by plausible reasoning rather than accurate perceptions (Weick, 1995). The data set to be preferred in strategizing is the one that can produce a plausible narrative. It is far from obvious that "more trumps better" (Mayer-Schönberger & Cukier, 2013, p.39); indeed, more may sometimes be less (Bollier & Firestone, 2010; Crawford et al., 2014; Naimi & Westreich, 2014; Nease, 2016).

6.4 Big Data Generates a Retrospection of the Past Rather Than a Prediction of the Future

Predictive analytics comprise a variety of techniques that predict future outcomes based on historical and current data (Gandomi & Haider, 2015). However, from the sensemaking perspective, data aids a retrospective interpretation of what happened in the past, rather than a prediction of the future (Weick, 1995). Managers often overlook the fact that nature of customers and markets are dynamic and enacted. When marketers use big data to predict, for instance, what their customers will do in future, they make the implicit assumption that the future will be like the past, and that it will change in some predictable way. The assumption may be warranted in stable social and market contexts, however in times of change this assumption is highly misleading (Satell, 2015a).

Well documented in the sensemaking literature are the dangers of relying on short term memory at the expense of long term recollection (e.g. Hartshorne, 1962). Big data exacerbates this tendency by offering strategists vast quantities of recent data and a relative paucity of historical data (Chatfield, 2016). This focus on the exponential rise in short term data, coupled with the assumption that future events will closely resemble recent experience can be highly misleading. As a result, managers' reliance on big data is likely to result in poor strategizing.

A case in point is the discovery that Google's big data Flu Trends (GFT) is no longer accurate at predicting flu. Although researchers (e.g., Lazer et al., 2014) blame GFT's method and data, we rather highlight that the dominance of short term retrospection is a major reason why forecasting and strategic planning can be

misleading if decoupled from the reflective action and long term memory (Weick, 1995).

In summary: from a sensemaking perspective, the basis upon which big data is being sold to managers, namely that data represents reality, that more data provides greater accuracy, and that data is inherently predictive, are unwarranted. Rather, sensemaking suggests that for strategic decision making, reality is enacted, plausibility of data will always trump accuracy, and that data can help retrospection only. In the next section, we consider how sensemaking perspective may help create alternative sustainable futures with big data.

7 How Can a Sensemaking Perspective Help Create Alternative Sustainable Futures with Big Data?

7.1 A Wake-Up Call

To summarize, a sensemaking perspective suggests that effective strategizing does not require nor produce an objective picture of reality, that strategizing is driven by plausibility rather than accuracy, and that big data generates a retrospection of the past rather than a prediction of the future. In other words, effective strategizing will be no better served by big data than by small data. Big data's potentially transformative power lies not so much in the characteristics of big data, on which its advocates concentrate, as it does in what big data's characteristics afford (Markus, 2015). Indeed, "[t]he myth and the tools mutually constitute each other, and the instruments of data gathering and analysis, too, act as agents that shape the social world" (Crawford, 2014).

More importantly, a sensemaking perspective reminds managers that big data is not the "inevitable consequence of a technological juggernaut with a life of its own entirely outside the social (world)" (Zuboff, 2015, p. 75). Rather, organizations are the creators of big data; to deny this is to succumb to the myth of the Big Other world (Zuboff, 2015); this latter narrative constitutes a new form of power that commodifies, controls, and affects behavior and daily experience in a way that gradually transforms human agency into automaticity. After all, it is organizations that act and create the materials that become the constraints and opportunities they face (Weick, 1995). We should realize that, big data is our tool, not our master. We gave them power, and we can take that power away (O'neil, 2017).

Although all technologies have 'dual effects' which is not inherently problematic (Markus, 2014), "the consequences of technology are rarely distributed evenly or equitably within or across stakeholder groups" (Markus, 2015, p. 58). For instance, whereas some businesses may benefit from using big data and algorithms, others may suffer. Facts show that big data does not benefit every company. The real concern is that the lion's share of big data benefits could go to a few large corporations, while individual citizens could suffer significant harm (Markus, 2015). In general, data is

owned and used privately to profit and influence, while the public is kept out of the process and told to behave well and trust the algorithm (O'neil, 2017). According to Zuboff (2019)'s projection, people are deceived and ignorant of the full consequences of surveillance capitalism, which is a form of data capitalism that derives value and profit through datafication and dataveillance of individuals such as consumers and worker. Since the social evolution isn't happening fast enough, we are facing a new kind of sovereign power from the Big Other to be unwittingly changed from human agency into automaticity. When all the behavior of persons and things are monitored and modified for profit and control, there will be no individuals. "Only the world-spanning organism and all the tiniest elements within it" (Zuboff, 2015, p.85) exist. Then, who and what will organizations become? How and by whom the profits and the power will be enjoyed?

7.2 An Inescapable Responsibility

A genuine sustainable future with big data, has as its goal *full* sustainability, rather than simply *slowing* the destruction of nature and society (Willard & Hitchcock, 2015). This is an inescapable responsibility for each organization in this society, regardless its size or nature. While making sense of big data from a sensemaking perspective, organizations are urged to recognize the role that they play in the creation and evolution of the big data era, so as not to let surveillance projects become institutionalized into society. Managers need to rethink how they view and use big data, and establish new precedents and laws to promote sustainability (Markus, 2015; Richards & King, 2014; Zuboff, 2015, 2019). As the Netflix documentary *The Social Dilemma* advocates, organizations and individuals can help shape how technology is designed, regulated and used. In a time when technology has become integral to our lives, it is more important than ever that we examine the role that big data plays in our lives and realign it with the interests of people and the environment, not simply profits.

Organizations should carefully consider their investment in big data. On the one hand, big data is, after all, not necessarily superior to small data, and it is not strategically inevitable. More than that, the creation of meaning in sensemaking is an attentional process, in which the attention is directed backward from a specific here and now (Weick, 1995). Yet, in an era of bigger and bigger data, the availability of time and attention from strategists is limited. Therefore, what strategists choose *not* to know, matters just as much as what they chose to know. On the other hand, the retrospective sensemaking of big data tells us that investment in big data contributes to demands for cloud services, which have already outpaced sustainable growth and created harms arising from computing research practices, such as the collection of huge data sets compiled from publicly accessible social media sites (Fiesler, 2021). Monserrate (2022) spells out the dangers that lie ahead if the Cloud is allowed to perpetually expand, unchecked by governments or publics. He also depicts a world in which tech companies continue to grow—seeking profits and remaining largely

unregulated—until the cumulative effects of their industry impact global warming to such an extent that governments and publics have no choice but to intervene, albeit too late.

Consequently, when considering big data initiatives, one caveat for organizations is that companies cannot pursue short-term profitability at the expense of environmental impact, economic equity, social democracy and individual freedom. After all, organizations consist of individual employees, who will have no escape from the unsustainable Big Other world. Rather, it is incumbent upon organizations to explore and advocate a legal, transparent, and ethical (big) data practice.

In order to use big data ethically, organizations must re-evaluate their metrics of success, which is often profit, efficiency, or default rates (O'neil, 2017). Whether a transaction is successful depends on what organizations count. For giant web firms, the click on the ad brings in a quarter, fifty cents, or even a dollar or two, which is used to measure success. Therefore, the system is deemed to be functioning efficiently. From society's perspective, a simple search for government services often turns poor people into targets, leading many to take out high-interest loans and receive false promises (debt.org). Lead aggregators lead them into needless transactions, leaving many of them with larger deficits and more dependent on public assistance. Despite the system's efficiency in producing revenue for search engines, lead aggregators and marketers, it operates as a leech on the economy.

Another example of corrupting metrics the maximization of 'time on site' through techniques such as A/B testing which results in addictive behavior by users (Davidowitz, 2018). Through such testing, Facebook, for example, may figure out what particular color of button and font get people to come back to their site more often. Then they change the button to that color and text to that font. They may also find out that emailing people at a certain time gets them coming back to their site more often, and they then follow so. Consequently, Facebook becomes a site optimized to maximize how much time people spend on Facebook. Similarly, despite the system's efficiency in maximizing the frequency of user's visit, Facebook operates as a leech on its users, breaking down users' self-control.

Sustainability thinking calls for organizations to understand all material, social and environmental impacts of the business, establish metrics to measure their success in managing those impacts while succeeding economically and scan the external environment constantly for threats and opportunities (Willard & Hitchcock, 2015). Therefore, a regulatory system should be set up to measure hidden costs by incorporating a host of values. It is necessary to impose human values on data algorithms, even at the cost of efficiency, even though concepts such as fairness and common good reside only in the human mind and can't be quantified.

In addition, O'neil (2017) pointed out that we should start building a regulatory framework to hold organization's data and algorithms accountable for the long term. In the same way that chemical companies must demonstrate they don't damage rivers and watersheds around them, companies that develop and deploy big data need to accept responsibility for their influence and develop evidence that they are not causing harm. They should be required to audit their data and algorithms regularly for legality and fairness. Of course, people with the skills to build data and algorithm auditing

initiatives are needed. Academic support for these initiatives is crucial. Their research tools can replicate the immense scale of models and retrieve data sets large enough to reveal the imbalances and injustice embedded in the models. In addition, they can build crowdsourcing campaigns to collect information about the messages people across the society receive from advertisers and politicians. This could illuminate the practices and strategies of micro-targeting campaigns.

Organizations can pro-actively spark and facilitate conversations about the harms of exploitative tech and what to do about it. In addition, they can grow coalition of business and consumers who are, say, boycotting their use of ads on social media until they stop valuing profits over hate, bigotry and disinformation. They can call for a ban on surveillance advertising—the toxic business model depicted in *The Social Dilemma.* While the societal awareness of the dark side of exploitative tech is raised, the public learns more about big data's inner workings and its prejudices. They will then demand more accountability from data and algorithm, while being more motivated to realign their relationship with technology as a tool for connection. For example, they will be mindful of data as well as the exploitative tech used to collect data. They will be able to be determined to take back control with the 7-day Social Media Reboot featuring tips from the experts featured in *The Social Dilemma.* They also will voluntarily help build and advocate for a more humane internet, and so on so forth.

In terms of governmental agencies, they play a powerful regulatory role and can start to adapt and then enforce the laws that are already on the books. Examples are used to illustrate this point in O'neil (2017)'s book. The Fair Credit Reporting Act (FCRA) and the Equal Credit Opportunity Act (ECOA) were meant to ensure fairness in credit scoring. The FCRA guarantees that a consumer can see the data going into their score and correct any errors, and the ECOA prohibits linking race or gender to a person's score. The regulations should be updated to avoid ignoring consumer complaints and explicitly prohibit credit-scoring companies from using zip codes as proxy measures of race. Consumers should have the right to know what information is used to calculate their credit score and to be alerted when it is being used to judge. Whenever there is an error, consumers shall be able to challenge and correct it. Another example is that, big data personality tests, health scores and reputation scores should not be able to sneak around the law to violate the protection of the Americans with Disabilities Act (ADA). On the other hand, government agencies shall make Corporate pledges enforceable to reduce harms to either the environment or society. Given the companies' financial ties to the fossil fuel industry and failure to meet the deadlines of previous pledges to reduce carbon emissions or other kinds of waste, scholars warn against entrusting "Big Tech" with its own regulation (Jardim, 2020).

7.3 Cultivation of 'Experiment for Learning' Communities

As action is a key sensemaking tool it is often wiser to begin with, and learn from, small experiments before broadening the action to drive change across a larger system (Ancona, 2012). Indeed, experiments are a form of 'action', specifically a form of 'acting thinkingly,' whereby managers 'simultaneously' interpret their knowledge with trusted frameworks, yet "mistrust those frameworks by testing new frameworks and new interpretations" (Weick et al., 2005, p. 412). People learn about situations by acting in them and then seeing what happens (Weick, 1985).

Big data makes randomized online experiments, which can find truly causal effects, much easier to conduct. However, the one so-called advantage of "you don't even have to tell users they are part of an experiment" (Davidowitz, 2018, p. 210), is manifestly unethical. What we advocate is enabling 'experimenting for learning' communities. Since companies learn only when individual skills and insights become embodied in organizational routines, practices, and beliefs (Attewell, 1992). Given information systems can change the fabric of social epistemology and the backdrop against which organizations construct, organize, store, distribute, and apply what they learn (Pentland, 1995), companies should focus their information systems on enabling experimenting for learning communities. In this kind of community, not only managers, but employees, customers and other stakeholders can use the company's data and their own knowledge to improve the firm's strategic performance.

The successful business strategy of 'listening to employees' at Best Buy (e.g. Tucker, 2010) presents a rubric for this principle. Years ago, in order to reduce employee turnover and raise their engagement and performances, Best Buy began experimenting with social networking technologies centered upon the company's intranet to create a deeper conversation with their employees across the United States and other countries in the world. When this strategy was activated, their employee turnover rate was 81% (Tucker, 2010). More importantly, this strategy was initiated by a mid-level marketing manager, Jennifer Rock, after she noticed that stores with high employee turnover rates and low employee engagement level suffered from poor sales revenue, while those with low turnover and high engagement showed strong sales performance. Through conducting weekly online polls of employees, setting up wikis for people with common interests to brainstorm together and organizing many other social media activities, Best Buy becomes skilled at communicating with its employees and connect employees with each other (Tucker, 2010). Ultimately, by leveraging networked communities in various forms Best Buy benefits greatly from both the loyalty and creativity of their employees and other stakeholders.

In fact, today there are many different types of social media that are used to support collaborative knowledge work, both within the firm and between the firm and its various stakeholders (Newell, 2015). Companies therefore should deploy these social media to foster flexible experiment for learning communities to further assist strategic sensemaking.

7.4 Incubation of Innovation

According to the sensemaking perspective (Weick, 1995), when strategists extract cues from the environment that triggers a drive to make sense of the situation, they use frames, the knowledge or mental structures that include rules and values, as a guide to understanding. When they create a relation between frames and cues, they create meaning (Miles, 2012).

On the one hand, the strategizing process in organizations is dominated by retrospective sensemaking, in which strategists introduce new constructs into the collective cognitive map of organization (Daft & Weick, 1984). They then put cognitive theories into action (Argyris & Schon, 1978; Hedberg, 1981). This new response or action based on the interpretation constitutes organization learning (Argyris & Schon, 1978). In so doing, strategists keep constructing and reconstructing the connections among their views of the past, present and future (Kaplan & Orlikowski, 2013). On the other hand, the dominance of retrospect in sensemaking is a major reason why forecasting, contingency planning, strategic planning and other probes into the future are often found misleading if they are decoupled from the reflective action (Weick, 1995). In a nutshell, their sensemaking is fundamentally about the new interpretation and understanding of the past, present and future, based on the newly emergent situation, though the distinctions between the past, the present and the future situations are too often to be ignored by strategists.

From the sensemaking perspective, data aids a retrospective interpretation of what happened in the past, rather than a prediction of the future. Therefore, the big data era is fundamentally different not for how much information it allows managers to collect for accuracy or prediction, but how it allows them to engineer systems to make new discoveries while making sense of the events and issues (Satell, 2015a). With that being said, the new paradigm of scientific method in an age of big data seeks to incorporate a mode of induction into the research design, although explanation through induction is not the intended goal as it is with empiricism. Instead, it forms a new mode of hypothesis generation before employing a deductive approach. In other words, it uses guided knowledge discovery techniques to identify potential questions (hypotheses) that deserve further examination and testing. Any relationships revealed within the data do not then arise from nowhere and nor do they simply speak for themselves. The insights are not the end-point of an investigation, but the basis for the formulation of new hypotheses. Put it differently, it is a reconfigured version of the traditional scientific method, providing a new way in which to build theory (Kitchin, 2021).

Recalling the legends of innovative marketers, such as Leo Burnett and Steve Jobs, we easily understand why innovation is important at any time. Big data should not be used to replace human creativity, but to inspire creative work or creative thinking (Elliott, 2014). This is why Unilever builds media labs in key markets that provide a platform for innovation, co-creation and incubation of new technologies in marketing programs (Unilever.com). This is also why it is promising for BloomReach to integrate technology and human intuition in its new application to allow marketers

to do their best to imagine and test new possibilities. As its marketing manager, Joelle Kaufman, says "A crazy idea isn't so crazy when you can calculate its effect without risking failure in the market." (Satell, 2014).

In addition, data analytics might also help marketers to re-engineer their ways of serving the customer. For example, the website of Neiman Marcus, does not serve their customers by predicting what its customers' preferences are, rather, the system puts its customers in control of their experience and assist them as them shop, by intuitively making suggestions much like a salesperson would do in the store (Satell, 2015b).

8 Conclusion

Over the last decade or so, the media hype around big data has created such a techno-utopia view of big data that it has driven companies to spend huge sums of money on data production and processing, in the hope of uncovering hidden patterns and generating deep insights (O'neil, 2017). Meanwhile, a heated debate over the negative social and environmental impact of big data has emerged.

Indeed, some researchers (e.g., Newell & Marabelli, 2015, Markus, 2015, Zuboff, 2015, O'neil, 2017) have voiced their concerns over the long-term impact of unparalleled tracking and extracting 'everydayness' (Constantiou & Kallinikos, 2015, p. 53) on individuals and wider society. This chapter brings a "sensemaking" (Weick, 1995) perspective to big data and its use in organizations, as strategic decision making is fundamentally a sensemaking process (Kaplan & Orlikowski, 2013; Weick, 1995).

A sensemaking perspective differs from the popular view of big data, and suggests that the basis upon which big data is being sold to managers, namely that big data is an inescapable trend, that data represents reality, that more data provides greater accuracy and that the data is inherently predictive, is unwarranted. Rather, sensemaking suggests that for strategic decision making, big data is created by organizations, it represents an enactment of reality, plausibility of data always trumps accuracy, and big data can only help a reinterpretation of the past. Examples are cited to illustrate these points.

Based on this sensemaking critique, we further discuss how a sensemaking perspective can help organizations to create alternative sustainable futures with big data. The sensemaking perspective suggests that big data's potentially transformative power lies not so much in the characteristics of big data, on which its advocates concentrate, as it does in what big data's characteristics afford (Markus, 2015). Managers should be skeptical of populist rosy mythology of big data and adopt a more sophisticate (and strategically insightful) sensemaking perspective.

We call for a more mindful view of big data. Also, we call for managers to actively curtail institutionalized surveillance projects (Zuboff, 2015). Finally, we call for a legal, transparent, and ethical (big) data practice with focuses on cultivating experimenting for learning communities and incubating innovations among individuals (their customers and employees).

This chapter makes two contributions to our understanding of big data. The first contribution is to offer a theoretical perspective to reinterpret the role of big data in strategic decision making, as well as the role organizations play in creating the big data phenomena. A sensemaking approach brings us return to the nature of strategic decision making activities and reveals what effective strategizing demands and what big data can and cannot deliver.

Second, this chapter follows the call for new critical approaches to big data (Crawford et al., 2014, O'neil, 2017) and the research on the longer term impact of big data on individuals and wider society (Monserrate, 2022; Newell & Marabelli, 2015). Therefore, it contributes to this growing critical conversation. The chapter brings a nuanced and grounded theoretical analysis to engage big data practices, tools, and rhetorics directly and ask how they function, how they build interpretations, and how they could be different, more ethical, and more historically aware.

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