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Management Misinformation Systems: A Time to Revisit?

Kalle Lyytinen
Case Western Reserve University
kalle@case.edu

Varun Grover
Clemson University

Abstract:

In this essay, we revisit Ackoff's (1967) classic "Management Misinformation Systems" and its five myths. The paper appeared at the dawn of the information systems (IS) field and shattered popular assumptions about designing and using IS. The paper shaped the direction and scope of scholarly discourse around information systems; in contrast to dominant claims at that time, he argued that managers swam in the abundance of irrelevant information, were victims of poor modeling and, consequently, poor understanding of their own decisions, participated in destructive communication due to conflicting goals, and had a poor understanding of how systems worked. Despite the passage of 50 years (and many revolutions in information technology), researchers in the IS field still regard Ackoff's arguments as valid and rarely debate them. Yet, given the new information-rich environments and our nearly limitless capability to collect and analyze data, we may need to reexamine these arguments to correctly frame information systems' contemporary effects on managerial decision making. We scrutinize Ackoff's five assumptions in light of today's IT and data-rich environments and identify key tenets that will reframe the disciplinary discourse concerning the effects of information systems. We identify significant shifts in research on decision making including the role of abduction, data layering and options, and intelligence augmentation. We honor the extraordinary legacy of Ackoff's remarkable paper as an IS scholar by shaping the field's future inquiries in the spirit of the original paper.

Keywords: Ackoff, Misinformation Systems, Information, Information Need, Decision Modeling, Big Data, Analytics, Overload, Relevance, Collaboration, Systems, Abduction, Data Layering, Augmentation.

1 Introduction

50 years ago, Russ Ackoff (1967) published a paper titled “Management Misinformation Systems”. As the title suggests, in the paper, he argues that management information systems (MIS) intended to provide information to managers were, in fact, misinformation systems. At the paper’s publication, MIS was at its inception, and the field was plagued by a failure to match growing expectations associated with the use of information technology (IT) in supporting managerial decision making (and, thus, the moniker “misinformation systems”). Similar failures were echoed in other papers’ titles of that era such as “MIS is a Mirage?” (for a review, see Hirschheim & Klein, 2012).

At the time of its publication, the idea of a periodic “push” of information to managers through automated reporting systems was giving way to a more novel notion in which a manager “pulls” information from the information system and its database. The manager’s decisions and related information needs would inform and guide this information pull. Accordingly, operations research (OR) and decision modeling had much influence on how the role of information was conceived during design and dominated the decision and data-analysis techniques needed to arrive at the decision. Researchers commonly sought to analytically model decisions and then build the “right” MIS that would optimally control manager’s decisions that follow. The decision models ultimately determined managers’ information needs and feeds. This approach was a new one, enabled by the power of the IT, around which managers’ information systems and the related decision models were built. This topic formed the key transitional theme that Ackoff (1967) debated (for similar arguments, see also Beer, 1972). At his argument’s crux, Ackoff exposed several erroneous assumptions in this decision-model view that pertained to the nature of the information environment that surrounded managers and its dysfunctional consequences for designing MIS and using them in decision making. In all, Ackoff identified five salient reasons (what he called “myths” of system properties and decision maker behaviors) for what researchers later labelled as MIS “failure” (Lyytinen & Hirschheim, 1987). Ackoff also put forward a counter thesis for each assumption that he analyzed as a baseline for more effective design intervention that IS scholars today would call a “design theory”’ Because the paper was novel in explaining the failures of IS and because it focused on theorizing around assumptions and concepts that guide and inform our understanding of the interactions between data, information, technology, and decisions, researchers have widely deemed it as one of the seminal pieces in the IS field (see, e.g., Hirschheim and Klein 2012; Dickson 1981). Further, researchers regard it as a classic scholarly piece, and many introductory doctoral seminars to the field still commonly require its reading.[1] Since then, a steady stream of empirical and theoretical work that has focused on IS use and implementation failures has extensively commented on, refined, and operationalized all of Ackoff’s theses (see, e.g., Lyytinen & Hirschheim, 1987; DeLone and McLean 1992). This research has resulted in richer and more nuanced understanding of how information systems operate in organizational settings and how they influence organizational and managerial action. It has also cogently delineated the multiple potential reasons for MIS failure.

Fifty years later, the growing power of computing is again radically transforming the information environment (Brynfjolsson & McAfee, 2014) and big data (Constantiu & Kallinikos, 2015; McAfee & Brynfjolsson, 2012; Davenport, 2012). Though we do not exactly define this new phase because it lies outside our scope here, several features characterize it: data’s volume, velocity, and variety and the massive computing power and analytics that allow new insights into managerial decision making and strategy. In Ackoff’s (1967) environment, volume was highly limited, velocity was not significant, and variety was small. Today, all these characteristics have dramatically changed, and, therefore, several authors claim that we have entered a period of transition in which the concept of information is expanding from structured text and numbers to unstructured text (words), images, emoticons, video clips, audio clips, narratives (increased volume/variety). The data comes no more under a priori defined categories because it includes unstructured data and covers more than expert-driven data collection and analysis practices. Now, it is often filled with “everydayness” dictated by user-driven semantics, folksonomies, and “nowcasting” (Constantiu & Kallinikos, 2015) (increased volume/ variety). Further, storage costs are extremely low and computing power is extremely high, which allows one to almost recklessly collect, clean, and store data (increased volume/velocity and data analytics). The computing power enables powerful visualizations and richer forms of inference

[1] Most IS scholars of our age have read this manuscript as part of the doctoral education if not earlier. It has also remained in many IS PhD capstone courses as an obligatory reading of the IS classics along with other papers such as Leavitt and Whistler (1958), Gorry and Scott Morton (1989), Dickson et al (1977), and Mason and Mitroff (1973). For a fuller recent account of these papers, see, for example, Hirschheim and Klein (2012). Several highly cited foundational pieces in the field have also echoed Ackoff’s (1967) work, such as Gorry and Scott Morton (1989), Mason and Mitroff (1973), and DeLone and McLean (1992). The current Google Scholar citation count for Ackoff (1967) is around 1868 of which 400 have accrued since 2010.

approaching, emulating, or reaching beyond human intelligence (increased variety/volume and data analytics). In addition, hardware, a resource to economize in 1967, is now cheap, connected, and scalable through the cloud to nearly any computation task, while software is highly modular, portable, and increasingly integrated (increased variety/velocity and data analytics). Finally, afforded by devices carried in one's pockets, briefcase, or bag, managers can now access data instantly and at any time and place.

Thus, given the order of magnitude change in IT functionality and data, how do managers now make decisions? How does the field fare with respect to Ackoff's (1967) fundamental theses? Are the false assumptions still corrupting our designs and use? Are they still relevant? Should we reevaluate, re-contextualize, and change them? Is his approach to critically assessing underlying assumptions that guide design and intervention still fruitful for IS research? With these questions in mind, we re-contextualize Ackoff's five theses in a contemporary design context in this paper. We posit that doing so is a particularly relevant exercise since 1) Ackoff focuses on managers' use of information—an important issue if not more so in today's information-replete environments, 2) it remains important to critically reevaluate the profound thinking from our field's past to evaluate its continued salience and re-contextualize it to the environment, and 3) we reapply and reanalyze Ackoff's theses to provide insights into research on (or the development of information systems for) "big data".

To address these issues, in this essay, we revisit the salience of Ackoff's (1967) ideas and re-contextualize his theses to the contemporary context to derive implications for future IS inquiries and practice. In doing so, we follow Ackoff's original format of analyzing assumptions. We present each key design assumption in Ackoff's paper and summarize his review of the original theses and his (counter) theses. We also demonstrate the salience of each of Ackoff's theses for IS design and use in practice and research. We then re-contextualize the original thesis and Ackoff's counter-theses to the current environment by introducing new concepts that characterize the contemporary environment. By doing so, we offer a foundation for a new argument that backs up the re-formulated and re-contextualized thesis. We also summarize the key tenets that characterize the new environment and that have resulted in the shifts in Ackoff's assumptions (counter-myths). We also discuss the future of IS inquiries into organizational decision making and the potential consequences of the proposed new theses for the IS field's theories and design practices.

To make our line of argument more palatable, we introduce concrete examples of changes in information, its use, and new types of decisions. We extract these examples from professional media and our recent field work that has focused on big data's use and its effects. We present these snippets of evidence as a means to concretely instantiate and illustrate new concepts and related claims we present. This is similar to the rhetorical strategy that Ackoff (1967) followed. Overall, our arguments represent an attempt towards what Corley and Gioia (2011) called prescience explorations where "the best way to predict the future is to influence the conversation about what it could or should be" (p. 24).

1.1 Design Assumption 1: The Critical Deficiency under Which Managers Operate is the Lack of Relevant Information

Ackoff's (1967) counter thesis: No, it is overabundance of irrelevant information and the necessity to separate relevant from irrelevant information.

Key concepts: Information overload, large sets of redundant documents, condensation, and filtration without loss.

1.1.1 Relevance for the IS Inquiry

This thesis is probably Ackoff's (1967) most-well known and widely cited one. It hits at the heart of information system design's purpose: should a MIS designer create systems that provide relevant information and, if so, then how should the designer determine what is relevant? Most requirements analysis methods, techniques, and even measures of IS impact rest on the umbilical cord between the idea of designing a system that provides relevant information and the effectiveness of managerial action (see e.g., Lyytinen & Hirschheim, 1987; DeLone & McLean, 1992). Ackoff points out, however, that such a design problem is too narrowly formulated and will have negative dysfunctional consequences for managerial action: the manager's problem in relating to information and decisions actually differs. It is a problem of choice: of separating relevant from irrelevant information in a mass of irrelevant information.

1.1.2 Ackoff's (1967) Argument for Assumption 1

When designers design MIS to provide relevant information, they pay attention to generating, storing, and retrieving a select set of *relevant* information using available technical means, such as constructing databases, coding, indexing, updating files, implementing access languages, and so on. The ideal, which emerges from this assumption, is an idea of an infinite pool of data into which a manager can, when the manager wants, dip into and pull out exactly the pieces of relevant information the manager needs. If, on the other hand, the designer sees the manager's information problem primarily as one that arises out of an overabundance of irrelevant information, most of which the manager did not ask for. The related design challenge then is to reduce information overload which introduces two instrumental goals for *any* information system design: improve information *filtering* (or evaluation) and *condensation* (see also Hiltz and Turoff 1985). Yet, in Ackoff's (1967) time, the literature on MIS seldom referred to these functions let alone considered how to carry them out. Since that time, such attempts have become prevalent as technology has matured, which we can see in the ideas and design of executive information systems, data marts, or more encompassing and flexible types of corporate data management (see e.g., Holsapple & Whinston, 1996). Yet, given the recent growth in data and processing power, we need to re-contextualize his thesis and reformulate it.

Contemporary thesis: The critical deficiency under which most managers operate is the growing inability to discover new relevant information from the mass of seemingly irrelevant information.

Key concepts: Ultra-Large heterogeneous data sets, unexpected tradeoffs between relevant and irrelevant data, attention and cognitive bias.

1.1.3 Our Argument

In Ackoff's (1967) world, the dominant economic logic and functional forms of information technology incentivized restrictions on the volume of data stored (e.g., batch processing, high cost of storage) and, therefore, limited data to what really was critical for designing an information system. Such constraining logic was prominent in the search for *relevant* information to be provided by the system. But, as Ackoff points out, such a focus ignored most data that managers dealt with daily, especially that data the designed IT systems did not contain. The idea at the Ackoff's time was, given the growing power of IT, to increasingly integrate all such data into the databases (now called ERP/CRM systems) and allow managers to filter and consolidate the relevant data and then analyze it so that managers would have information at their fingertips, so to speak (see, e.g., Holsapple & Whinston, 1996). That goal has now come to fruition: managers today can largely filter and consolidate enterprise wide data, which has resulted in the excessive information overload that Ackoff rightly anticipated. Accordingly, as Ackoff noted, managers now spend a "great deal of time separating the relevant from the irrelevant (p. Ackoff ,1967 B148)".

Not surprisingly, the vice of information overload poses a grand challenge for today's management, and it will remain so long as the amount of information stored, exchanged, and communicated continues to grow exponentially (see, e.g., McAfee & Brynfjolsson, 2012). Yet, it would be too easy and simple to gloss over the differences between Ackoff's (1967) environment and the current one and just argue that the overabundance of irrelevant information is now a bigger problem. Managers are now more challenged by separating relevant from irrelevant information for their decision making. However, an important distinction is that the problem is not any more one of filtering but rather one of discovery. This has important manifestations for contemporary organizations as we discuss below.

Given the changes in the information environment, the challenges for information overload are moving beyond the questions of condensation and filtering in systems' design (Speier, Valacich, & Vessey, 1999; Hiltz& Turoff 1985; Jones, Gilad, & Sheizaf, 2004). If that were not the case, one could not add anything to Ackoff's (1967) original argument. We now have much larger pools of data and have more versatile ways of analyzing them that solving information overload does not anymore call for a change in quantity but rather perhaps in quality. Managers today face an emerging and more fundamental challenge[2]: they do not only need to know what to pull and condense as Ackoff suggested but also know how to extract novel, unexpected insights from big and heterogeneous data pools. One no longer decides data's relevance when designing an information system or prior to searching for data to perform a decision task. Rather, its

[2] If today's core thesis was the overabundance of irrelevant information, then this would direct our efforts into sophisticated filtering mechanisms at the source so more relevant information can be captured. In our opinion, that would help, but would not address the more important problem, which is now more the post-hoc determination of the relevance after the data has been inexpensively captured, stored and possibly aggregated.

relevance results from dynamic and extensive data-related inquiry. Because data sets can now be both external and internal to an organization and their meaning and scope is not necessarily under a designer's control (or defined in terms of an enterprise-wide database), dealing with information overload now increasingly concerns making sense of and giving sense to new forms of heterogeneous data sets.

As we note above, one can now collect and store data cheaply. Therefore, organizations and managers are increasingly hoarding larger swaths of data. This process is also being accelerated by the emergence of new sources of data in innovative frontiers expanded by location-based data and the Internet of Things (e.g., see McAfee & Brynfjolsson, 2012). Also, one can transfer and integrate data more cheaply and easily thanks to standardized application interfaces (SOAP, REST), data definition and transfer standards (XML), and cloud services. However, generating deeper insights into the walloping sea of data is becoming a new, true challenge. Today nothing and everything is irrelevant in data; the idea of information depends more on what one can meaningfully extract from the data *contextually* so as to build local theories of the situation that make new alternative courses of actionable. As one manager told Williams, Boland, and Lyytinen (2015) recently on his uses of "big data": "we…need to come at our data and everything it holds with a sense of wonder and astonishment, and…being open to surprise as to what might come about or what might be there".

Hence, the new critical deficiency under which managers operate today is their inability to discover new relevant information by continually building and revising cognitive frames that help give sense to the data. This deficiency calls for managers to constantly question their current domain assumptions and diversify and integrate pools of knowledge that help in sense making. However, several issues aggravate their ability to do so: 1) powerful storage and access technologies that exceed one's ability to master (i.e., capture, integrate, analyze, disseminate) the data, 2) the increasingly diverse scope of information whereby one can combine and transform seemingly disparate and originally irrelevant pieces of information into meaningful information, and 3) as a consequence of the second point, increased threats and/or opportunities in finding confounding or random connections in the data. For managers and designers alike, it is difficult to foresee relevance a priori since one can now combine data in a nearly infinite numbers of ways, which results in a larger number of false positives. As one manager told Williams et al. (2015) recently: "To be honest, I didn't even know I could get this kind of information out. But when I realized I could do it, I was able to ask a lot more questions."

Following Ackoff's (1967) presentation format, we now provide examples and consequences of the new challenge. For example, a retail manager who engages in systematic data mining can now parse out the profitability of individual product lines or even products with relative ease using historical sale and cost data; these actions exemplify filtering and condensation. While ranking products based on profitability, the manager might conclude, based on "rational" piecemeal calculus, that high-end (expensive) products that show consistent losses need to be purged. They just consume valuable capital and do not yield commensurate sales. The decision, however, might turn out to be absolutely wrong if one carried out broader discovery-focused data analysis and exploration that goes beyond filtering and condensation. More broadly analyzing the data set in this example would call one to examine *the relationships* between the sales of different products over time and could yield an alternative conclusion. A product being purged could actually attract high-end customers into the store and promote the sales of cheaper, high-margin products. Therefore, purging such products could in the end result in net losses for the company (Helm, 2008)[3]. Hence, to identify relevant and irrelevant data requires that the decision maker casts the data net more broadly and seeks to constantly discover new meaningful relationships.

Even in organizations that have a strong analytics culture that integrate the understanding and use of algorithms, automated processes, and metrics, it is difficult to distinguish between unbiased or biased patterns due to people's changes in behavior when the metrics are in place. For instance, in highly analytics-based policing systems, police officers that are judged based on their number of arrests performed might focus more on the metric than broader issues of reducing crime or engaging in impactful investigations. The data reinforces the "fact" that they are doing a good job, while, in reality, the data might simply indicate that they are pandering to metrics (Moskos, 2009). Such biases may be implicit in all data sets and be more important when decisions are increasingly data driven. For example, companies that look at historical hiring data to predict characteristics of "good" employees may, in fact, be just reinforcing past prejudices in hiring decisions—particularly if some variable tied to job performance is associated with race, gender, or ethnicity (Barocas, & Selbst, 2014). Even data collection that has been in place over long periods might be subject to such local biases. For example, for over 20 years, the state of Virginia has collected data on student

[3] Tesco indeed decided to retain its money-losing product, milk loaf bread, when it realized that the product attracted high-end customers that were highly profitable for the company.

enrollments, aid, degrees awarded, and so on, but the data reported by different institutions and at different points in time have different meanings associated with these variables. For instance, when the state recalibrated SAT scores, some institutions might have used older calibrations or stopped collecting this data for certain students (Korolov, 2015). Netflix tries to alleviate such biases in its recommendation algorithms by splitting the data in half—one half to develop and enhance the algorithm and the other half to test it.

Managers need to also overcome the threat that they can treat data in their decision contexts as “natural” phenomena rather than as artificial, semiotic means through which one captures, describes, and prescribes a “slice” of (mainly social) reality. Therefore, one needs to understand how data relate to an actual phenomena of interest and how the data “construct” a specific sense of that reality needs. Data is never the same as the actual social phenomenon. For instance, managers need to ask to what extent the sentiment analysis of social media messages captures the actual feelings of people about a product in question. Or, alternatively, they might ask if sentiment analysis is just a way of figuring out (through aggregating and processing) generalized attitudes about the product as they are expressed in the chosen online social media.

In sum, in order to discover meaningful information from the vast repositories of seemingly irrelevant information, managers need to leverage broad patterns of data, alleviate false positives through tools and critical thinking, and recognize and alleviate inevitable data bias. Key tenets of these contemporary challenges include:

1. **Seek to make irrelevant data relevant.**

During Ackoff’s time the designer made the decision about relevance during the initial design of the system and to avoid missing relevant data he or she expanded the data set so that manager was inundated with irrelevant data. Now the designer needs to assume that no information is potentially irrelevant. Hence, he or she must address the concern for how to separate relevant from irrelevant data when arriving at the decision.

2. **Use a broad in contrast to a narrow net for data.**

Due to the low cost of collecting data, it is increasingly appropriate to not sample but use complete and expansive data sets. Data can be expanded and organized during system use and the largest problem is to create relevance out of irrelevance through new combinations and analytics. Therefore, it is beneficial to cast a wide net to discover relevance. Due to both the low cost and wide access to ultra large data, one needs to reassess data’s value in terms of its option value (Fichman, 2004). Sometimes, collecting data at infinitesimal costs may yield great insights at the opportune time. Of course, regulatory or ethical concerns for privacy (e.g., such as issues around creepiness) constrain what data one can collect (Stevens, 2016).

3. **Combine flexibly analytics, visualization, and critical thinking.**

Understanding basic elements of hypothesis testing, correlation and causality, and experimentation, along with strong analytical tools and culture help mitigate false positives. Such findings often dissipate a manager’s energy in vain. Visualization helps overcome complexities in discovering new relationships in data by suggesting alternative angles to explore it from (Williams et al., 2015).

4. **Recognize and overcome bias in data.**

Given the increased diversity of both soft (e.g., social) and hard data, the decision maker needs to be aware that data always come with inherent biases and can implicitly or explicitly serve political or parochial agendas. As such, one needs to store and communicate “meta-inferences” of the data rather than data itself. Even evaluations of products and services can now be subject to biases and herd effects (i.e., users’ providing good ratings because other ratings are positive). Recognizing biases and de-biasing data, whether it is ratings or a Google search, has become a critical element of the contemporary data environment.

1.2 Design Assumption 2: Managers Need to be Given the Information They Want

Ackoff’s thesis: No, for managers to know what information they need, they must be aware of each type of decision they make and must create an adequate model of each. Without a model, managers play it safe and ask for too much information.

Key concepts: variable selection, model specification, one good versus many poor variables, explanatory power.

1.2.1 Relevance for IS Inquiry

This thesis is another well-known claim from Ackoff (1967). It addresses the challenge that designers face: what criterion determines relevance at the design time? How can the designer come to know what is relevant for a manager in order to design the supporting system? Most requirements-analysis methods and techniques dictate that designers should be asking managers what they need (Ackoff, 1967). Ackoff points out, however, that this design criterion is too narrowly formulated and will have negative dysfunctional consequences for managerial action.

1.2.2 Ackoff's (1967) Argument for Assumption 2

According to Ackoff (1967), managers rarely can articulate the conditions that they use to evaluate whether their information need has been satisfied. Most managers have some conception of some types of decisions they must make but not all of them. Moreover, their conceptions of the decisions they make are:

> *likely to be deficient in a critical way—a way that follows from an important principle of scientific economy: the less we understand a phenomenon, the more variables we require to explain it. Hence, the manager, who does not understand the phenomenon will "play it safe" and wants "everything" with respect to information creating overload. The MIS designer, who has even less understanding of the phenomena facing the manager then tries to provide even more than everything* (emphasis in original) (Ackoff, 1967, p. B149).

As a result, large data output emerges from the IS design process. Without good models of decisions, IS designs will have a tendency to overload managers with more irrelevant information.

Contemporary thesis: Managers need to gather all information they can in order to discover what they truly need in emerging decision situations.

Key concepts: performative business processes, automatic execution of business models, second-loop learning, business experiments, analytic talent.

1.2.3 Our Argument

In Ackoff's (1967) world, to determine a manager's information needs, the designer needed to correctly model decisions by abstracting a set of factors impinging on managerial decisions. After such an exercise, managers would know what data they really needed (see also Beer, 1972). Critical managerial decisions today are rarely well bounded (though we doubt they were so even in Ackoff's times). The ones that were operational during Ackoff's time are now largely enacted by automated models and related 'performative practices' scripted into systems and IT-enabled business processes. Business processes have now become truly performative in the sense that they enact a priori designed business models and logics that have been automated by using databases (including social data), increasingly sophisticated decision rules, and integrated workflow systems (MacKenzie, 2006).

However, second-level feedback loops and continued innovation around products, processes, and customer experiences generate now increasingly unstructured and emergent decision situations. Managers need to gather all sorts of diverse information broadly around the decision context in order to determine through a discovery process products' and services' actual desired features and customers' needs (David et al. 2012). The gap between wants and needs in this case is never solely an analytical problem; rather, it is a data-layering and sense-making problem where one layer of data influences (or provides options to) how one understands, views, and values another layer. During this process, data induction and abduction become critical. Inducting data refers here to making sense of data by categorizing it; abducting data refers to defining a problem, revising it based on growing evidence, and solving it as a decision outcome. If done correctly, data induction and abduction provide better outcomes than the construction of a priori, limited deductive models of decisions or testing existing deductive models with incomplete data. Resolving the inductive problem requires not only analytical tools and thinking, but also creative and lateral thinking, diverse analytical talent and skills, and openness to fresh insight and foresight. This process might involve recognizing that any boundaries set on the data or problem may provide only local optimal solutions that differ from the broader or more global optima.

Next, we review several examples and consequences of these new challenges. Even though companies' ability to collect data now far exceeds their ability to mine it for discovery, today's changed data economics dictate the scope and possibilities of capturing data. Reaching beyond their own data, companies can now target outside sources for both data and analytical capabilities. For instance, Hertz now supplements its in-house data with software from IBM and Mindshare Technologies, which provide an analytic engine to decipher thousands of social media comments from Web surveys, text messages. and emails to pinpoint and make sense of customer problems (CIO, 2015). Amazon keeps data around forever: "We never throw away data." (Jeff Bezos, in Rao, 2014). Amazon management believes that one only can determine data value in the longer term, not at the time of capture[4]. Twitter integrates its social and mobile data through its recent acquisition of Gnip (Kepes, 2014). In some cases, one can cultivate valuable data sets by conducting digital experiments. For instance, LinkedIn did not run analytic models to predict traffic for their "People You May Know" application. They just ran a set of experiments to test its efficacy. When they realized that the click through rate based on this application was substantially higher than other ads bringing customers to LinkedIn, they rapidly made it a standard feature of the website (Davenport, 2014).

The ability to leverage big data depends on an analytical mindset. Managers accustomed to making decisions on gut feelings may not feel comfortable with data and, worse, may discard important data based on their intuition (McAfee & Brynfjolsson, 2012). As one manager recently told Williams et al. (2015):

> *I think often about how narrowly focused people can be but also about how making data available and democratizing it has a huge effect on the attitude and the trust and the extent to which people are just going to believe you when you say something… the data you put out is the same data for everyone. You can't spin the information for one group of people because everyone has access to the same stuff!*

A case in point is a large European manufacturer of chemical products that had hired a new CEO who wanted to have employees work in a more evidence-based way. However, before building a large data-driven customer management system, they went through a major exercise using data analyst teams to improve the way employees accessed and used data. The company rolled out the CRM system only after salespeople accepted the need to work in an evidence-based way (Marchand & Peppard, 2013).

Another element of the new environment beyond the analytical mindset is the incessant quest to identify needed data based on actionability. Evidence needs to warrant using data sets and inferences. Accordingly, one needs to put insights derived from large data pools into action immediately through experimentation before causality can be distinguished from correlation (Williams et al., 2015). However, one cannot execute such actions before the relevant information is available, which creates a catch-22 situation. In sum, a passive approach to data will result in convenience samples, biases, and limited insights: active engagement is needed to identify relevant data, overcome biases, and generate new insights into what data one needs.

In sum, to truly grasp a manager's information needs in the current information-rich environments, managers need to be open to harnessing data and analytic talent from various sources and exert an analytic and action-oriented mindset towards data. Key tenets of this view include:

1. **Widen the distance between data capture and data use.**

During Ackoff's (1967) time, data was captured for a single purpose and resided in one system. Now, the data is integrated and can used for a myriad of purposes, including contexts that one cannot determine a priori. The distance between when one captures data for one purpose and uses data later for other purposes grows all the time. Accordingly, designers and managers need to capture and assess data for multiple potential future uses that give it increasingly an option value.

2. **Diversify the analytical talent of managers.**

Creating value from "big" data comes with inherent randomness and complexity: data's value will inevitably vary across companies, situations, and managers. Moreover, few managers have the analytic ability and great insight (Shah, Home, & Capella, 2012), which calls for implementing processes and building an analytic mindset to facilitate data innovation and mitigate such randomness. However, doing so is hard, because it challenges managers' standing and their pre-existing and invested domain knowledge.

3. **Make Information needs actionable using intervention, experimentation, and external sources.**

For emerging decision situations (e.g., new products and services), one does not need an explanatory model of decisions or outcomes because they will become a constraint. Rapid actionable intervention using experimentation often provides the best path to assessing data's value. Ironically, with the access to vast external data resources such as through social networks, managers can now gather rich information to hone their wants and, thereby, reduce the equivocality of their information needs.

[4] There can be some limitations to this principle regionally as some states and regions regulate how long the data can be kept depending on the purpose of using the data. See, for example, EMSA (2015).

1.3 Design Assumption 3: If Managers Have the Information They Need, Their Decision Making Will Improve

Ackoff's thesis: no, most management problems have too many possibilities to expect experience, judgment, or intuition to provide good solution guesses, even with perfect information.

Key concepts: decision complexity (i.e., too many computations or probabilities), decision rules, performance feedback, learning by doing.

1.3.1 Relevance for IS Inquiry

This thesis derives from and expands Ackoff's (1967) first two assumptions. It addresses the challenge facing a designer even the designer can deliver the information a manager wants: that is, that the manager's decision making performance may not still improve. Information is necessary but not solely sufficient for improving decision making. Most requirements-analysis methods and techniques stuck to this assumption at Ackoff's time: deliver the information and the right decision will follow (Ackoff, 1967). Simplistic approaches to determining requirements today may still assume the same. Ackoff already pointed out, however, that this criterion is too narrowly formulated and that designers may have to look for additional sufficiency conditions to improve managers' decision making.

1.3.2 Ackoff's (1967) Argument for Assumption 3

OR's own history contradicts this design assumption. For example, if one gives managers an initial tableau of a typical "real" mathematical programming, sequencing, or network problem and see how close they come to an optimal solution, then, as Ackoff (1967, p. B150) notes: "If their experience and judgment have any value they may not do poorly, but they will seldom do very well". Therefore, information is only valuable if it is augmented with right types of (analytic) decision models and decision feedback.

Contemporary thesis: Ackoff's (1967) initial thesis still holds. However, fast feedback and new forms of discovering decision rules improve decision making at a different scale.

Key concepts: data analytics, decision rule discovery, adaptation, data versus judgment tradeoffs.

1.3.3 Our Argument

In Ackoff's (1967) world—which originated from the traditional OR view—managers did not really understand such things as linear programming problems and related techniques (such as the simplex method) that informed many of the operational decisions of the day. At the same time, their judgment alone could not deal with such complex problems. Therefore, they found it difficult to improve their decisions because their intuition ruled. They could not support their better decisions by discovering new decision rules and obtaining fast feedback on their performance.

Over time, managerial decision models have grown exponentially more complex as the computing capability to solve large OR and other analytical problems have expanded. Further, computing capability has expanded due to several improvements in topics like improved algorithms, new heuristic techniques (such as machine learning or genetic algorithms), and access to vast computational resources (speed / memory). In other words, models now replace judgment in situations that one could not compute or easily analyze before. For such problems, judgment alone does not truly help improve decision outcomes even when one has the right information. Rather, to discover new decision models and rules, one needs to be able to formulate adaptive, learning-based models for decision processes through experimentation (see, e.g., Luca, Kleinberg, & Mullainathan, 2016) and use clever algorithms combined with brute computational power and big data. Such actions go far beyond Ackoff's (1967) primarily deductive approach to articulate decision rules. In contemporary environments, data-savvy managers need to leverage constant trials with big data and use multiple inferential and visualization mechanisms to discover decision models and rules that can enhance or replace judgment (McAfee & Brynfjolsson, 2012; Luca et al., 2016; Williams et al., 2016). This change has called for inventing increasingly powerful ways to explore, discover, and improve decision rules. The challenge now is how to actually help managers better discover and experiment with decision rules.

We next review examples and consequences of these new challenges for decision processes. For example, a manager may still "feel good" about a new product launch the manager's company has just introduced after a careful market analysis and analytic process of optimizing product features and manufacturing cost. However, one might ask whether this process could truly substitute for a post hoc sentiment analysis of millions of tweets, texts, and conversations on social media that might get at the customer's true feelings about the product. Further, one might ask how one can garner such data into new decision rules about product features and their diffusion. Over time, learning adaptively from the customer data and behaviors will likely result in much better decision performance around product innovation.

Indeed, evidence about performance differences between relying on individual judgment and using complex data analytics applied on heterogeneous and large data sets has recently started to grow. Several recent studies document data analytics-based approaches' superior performance when one faces such complex decisions. These cover parole decisions, analyses of x-ray images, and even predictions of the U.S. Supreme Court's votes (McAfee, 2013). Similarly, in the domain of legal discovery, several studies have recently shown technology reviews' superiority over human reviews (Catalyst, 2013) Studies focused on identifying new product ideas have found that intuition-driven managers wrongly emphasize feasibility, while customers prefer creativity, which one can best learn from consumer-related experiments (Mueller, 2014). Shaw (2014) discusses a competition run at Harvard where a statistical model based on six crude variables from a huge number of historical cases could predict the U.S. Supreme Court's decisions far better than the qualitative judgments of 87 law professors. Similarly, in a recent case focused on hiring decision performance, a simple equation outperformed human intuition again by a fair margin (Kuncel, Ones, & Klieger, 2014). Even in the soft, experience-driven and human-side world of dating, Match.com draws from its billions of data points and more than 15 matching algorithms to make matches instead of relying on expert judgment and has significantly outperformed its competition (Kiron et al., 2012).

Research has also shown a hybrid approach where managers augment their judgment with data to be problematic when the managers apply the judgment to the model ex post instead of ex ante (Luca et al., 2016). A symbiotic and adaptable approach, where managers dynamically provide inputs to the model and then rely on its outputs for decisions where they can adjust the decision criteria on the fly, offers the best performance (McAfee, 2013). For instance, Intel uses judgment to determine an initial set of variables that can predict market performance of its products in allocating R&D funds and then uses advanced analytics and visualization tools with outputs that managers interpret. This has transformed the company's R&D portfolio approach from an arbitrary process based on judgment to one that is more objective and predictive based on analytics and hard numbers, buttressed with judgment.

In sum, data analytics and visualization now replace either pure deductive OR models and pure judgment and can improve decision performance. To enact this change is a new challenge. Tenets of the more contemporary view include:

1. **Big data analytics offers new ways to learn from and improve past decisions.**

The big data analytics changes decision analysis and decision making into a continuous learning processes enabled by data, data analytics tools to discover, try out and learn about decision making that is adaptable and symbiotic.

2. **Move constantly the tradeoff between judgment (the highest paid person's opinion (HIPPO)) and analytics toward analytics.**

Data and analytics always beats no data and opinion**.** But changing the culture from a HIPPO culture to one based on data-driven analytics can be difficult (Luca et al., 2016; Williams et al., 2015). It requires changing the decision mechanisms at the core of the organization from expert judgment to analytics and data-based decision making (McAfee, 2013). Judgment and intellect are still critical at the two ends of the decision process, which includes framing the problem in a novel way and determining how to implement the decision. But, during the decision process itself, one needs to discover and justify decision rules and learn from them in an adaptive way in the new environment.

3. **Simple big data analysis on complex problems can substitute (not complement) for judgment.**

New tradeoffs between analytics and judgment have also emerged. Simple methods applied to massive data can often provide better results than traditional complex models on "small" data (Kirkland, 2014). The former can often substitute for the judgment[5], while the latter complements it.

[5] Even here, with massive data, significance levels are not meaningful since there is no type I or II error. However, one might need to assess the practical value of the strength of relationships in the data (effect size).

1.4 Design Assumption 4: Better Communication between Managers Improves Organizational Performance

Ackoff's (1967) thesis: better interdepartmental communication enables managers to coordinate their decisions more effectively and improves the organization's overall performance. However, communication does not necessarily achieve these effects and factually seldom does so if the organizational structure remains the same.

Key Concepts: communications, organizational structure, performance measures, number and power of organizational units

1.4.1 Relevance for IS Inquiry

This thesis addresses the challenge facing designers when they deliver the information managers want, which includes data about other units and organizational processes. In such a situation, delivering such information will not necessarily optimize that the overall organizational performance, nor will all managers necessarily agree on the decision made based on that information. Most requirements-analysis methods and techniques stuck to the assumption of political neutrality at Ackoff's (1967) time: share the information and managers will make the right information. Today, simplistic approaches to determining information requirements for managers still assume the same canon. However, Ackoff already criticized this assumption in that it is too narrow and simplistic; the designer will have to look for additional structural and power-related conditions to understand actual decision outcomes.

1.4.2 Ackoff's (1967) Argument for Assumption 4

Organizational units have conflicting goals and associated measures of performance. As such, the goals will imply that the measures constantly battle with each other. In such cases, guile will drive communication between departments and hurt the organization's overall performance. Generally, managers will not share information that harms their interests, and they will not improve their decision making outcomes by using such information. Accordingly, one needs to consider organizational structure, effective performance measures, and incentives before opening the flood gates of data. Broadly, the free flow of information between different parts of an organization is a fantasy given the structural constraints, power and incentives influenced by doing so.

Contemporary thesis: sharing information and analytics across functions and outside the organization, when structural performance measures conflict with each other inevitably changes the dynamics and scope of organizational communication. By being shared, however, the data will more likely lead to joint problem formulation and decisions based on shared evidence.

Key concepts: coopetition, information sharing, visibility, absorptive capacity, innovation.

1.4.3 Our Argument

In Ackoff's (1967) world, organizations' structure featured rigid functional departments that competed over scarce resources and operated under relatively fixed functional metrics that separately evaluated the performance of each unit. Therefore, each unit's goals and benefits conflicted with each other and sharing data did not improve organizational communication. Today's organizations are increasingly flat, dynamic, and guided by generic process metrics that cut across departments and functions. Accordingly, though competition over scarce resources and conflicting performance objectives remain in place in today's organizations (often out of necessity), the process orientation and related metrics have created a need for managers to cooperate and compete simultaneously—often at different levels and in different contexts. Therefore, they need to share information and analytics with partners and managers founded on common definitions for data sets. Sharing information promotes greater absorptive capacity, streamlines operations, and provides better visibility for issues and problems and, thus, incites innovation. As one manager recently told Williams et al. (2015):

> *I think just having a level playing field and having community access to the data and to the views, organizationally, is a good thing. Everybody sees that you are being measured, everybody sees that there's one version of the truth, everybody is pulling from the same source. I think that's been key here.*

Hence, though conflicts exist, managers are more likely to address organizational decisions through jointly shared evidence and analytics rather than pure power play, guile, and HIPPO. Managers can and need to reveal data and explore it to set new goals and, thus, generate new types of shard decision processes.

Several recent examples attest to the presence of these new challenges. A survey of more than 1200 executives globally in 2013 rated “getting business units to share information across organizational silos” as the top challenge in getting business value from big data. When managers across functions collaborate around such data-based analysis, the resulting client services are superior, less susceptible to commoditization, and generate higher revenue (Gartner, 2015). At companies where marketing and IT collaborate highly (e.g., Western Union and Adobe), analytics forms a big part of the culture. Spectrum Brands, for example, now blends HR and financial data to resolve conflicts between hiring and personnel cost because the analytics provide better insight on what decisions around hiring and compensation entail. Further, knowledge sharing coopetition arising from data and analytics sharing promotes innovativeness and increases the value of cross-functional coordination (Galunic & Eisenhardt, 1996; Tsai, 2002).

Even between organizations or institutional fields in which functional competition reigns, growing data sharing has contributed to innovation and improved performance. For instance, Uber has been successful in its strategy in part, because the platform allows drivers, service providers, and customers to share significant amounts of data, though these stakeholders do not share the same goals. Health organizations that compete for grant dollars now cooperate in data analytics to support research in the U.S. National Cancer Institute’s clinical research centers. The explosion of DNA sequencing data and tools has made the companies realize that too much data exists for any individual laboratory to handle; instead, working together and sharing information and building the supporting infrastructure will expand the efficacy and research outcomes. As such, many research enterprises are now transforming from “working in silos” with competing measures of performance (e.g., grant dollars) to participants in communities who simultaneously compete for dollars and collaborate through big data (Overby, 2014). In sum, open communications around shared data even under conditions of conflict result in greater efficiencies and stronger innovation. Tenets of the contemporary view include:

1. **Structure decision processes in dynamic and process-oriented way offering a context for joint data sharing.**

Decision makers need to share information and analytics with partners and managers founded on common definitions for data sets and enable achieving shared process goals. Sharing information promotes greater absorptive capacity, streamlines operations, and provides better visibility for issues and problems and, thus, incites innovation.

2. **Build on prevalent coopetition**.

Today’s business involves cooperation at one level and context and competition at another level and context. Sharing information on dimensions that promote joint decision making and keeping information proprietary for competitiveness is a fine line that organizations need to draw constantly. Organizations need to understand the impacts of differential levels of information asymmetry and their related costs and benefits to effectively make decisions.

3. **Promote micro-coordination based on real-time information.**

Communicating more information reduces structural inefficiencies in resource consumption because individuals and firms can now micro-coordinate based on the shared information of a situation, achieved through data sharing and emergent transparency of interpretations. This particularly holds when common processes cut across multiple local contexts and real time adjustments are needed.

4. **Share information to generate common analytics frameworks and metrics.**

Sharing information facilitates a common analytics culture across functions, and has now become critical for improving the overall organizational performance of big data initiatives and decision making.

1.5 Design Assumption 5: Managers do not Have to Understand How the Information System Works—Only How to Use It

Ackoff’s thesis: no MIS should ever be installed unless the managers who will use it receive training to evaluate and, hence, control it rather than be controlled by it.

Key concepts: understanding system design, management control, delegation of control.

1.5.1 Relevance for IS Inquiry

This thesis addresses the important challenge facing any manager in making a decision about an information system. This decision shapes also consequent designer-manager interactions. It also raises the issue of determining a manager's or designer's specific responsibility in making decisions through using the system: is it to understand how the system works, to understand it at a particular level of detail, or to understand how it may impact organization and decision making? Or, is it to make sure that the system provides managers with the information they want? In Ackoff's (1967) time and even today, managers have bypassed many system impact analyses for a superficial declaration that the manager needs only to get relevant information from the system in an "easy to use" manner. Ackoff (1967) however, strongly criticized this view to the extent that he stated that a system should not be installed unless a manager understands how it functionally works.

1.5.2 Ackoff's (1967) Argument for Assumption 5

In failing to evaluate MIS because they fear showing incompetence or because of other ulterior reasons, managers delegate the need to understand the system functions and related business logics to designers (who rarely understand them either). As a result, the systems' designers ultimately possess much of the organizational control of the system's functions. However, as Ackoff (1967, p. B152) notes with irony, these individuals "may have many virtues, but managerial competence is seldom among them".

Contemporary thesis: managers cannot understand how systems work anymore, but they need to know how to make them work in their business domain.

Key concepts: decision models, analytic products, speed of decision making, outcome orientation.

1.5.3 Our Argument

At Ackoff's (1967) time, managers made decisions about relatively isolated and well-defined systems such as inventory control systems (the example Ackoff used). As Ackoff pointed out, in such environments, managers needed to understand how their systems work (i.e., their functionality and underlying business logic). In today's environments, system complexity has grown to a level that makes such an understanding infeasible for most systems (such as ERP or CRM systems). These systems now provide detailed and interconnected business logic that goes far beyond the purview of the manager's domain. They also offer a large variety of alternative business logic even for the same business functions. Accordingly, managers face the challenge of matching their understanding of the relevant business logic to the one inscribed by the system. Only reducing this gap allows managers to recommend changes to the business logic enforced by the system when it does not work. Again, managers cannot transfer this responsibility to designers who neither have the managerial competence nor related responsibility. Since managers today need to sense and respond to business opportunities expediently, associated decision making requires quickly honing to business rules and logic that work without necessarily investing too much time on why something works.

Correspondingly, another related change in today's environment is that managers need to observe novel data patterns and, thereafter, carry out rapid business experiments that involve changes in the business logic. They need to also examine consequent patterns of business flow to determine whether the changes worked and then change the system accordingly. Such experiments provide strong evidence of causal logic, which is the means for improving business models and performance. As more analytics get built into business processes, managers need to also understand the general logic of those models and their implied cause-effect patterns. Managers here need to rely on extensive analytical toolsets such as ESS or DSSs and, therefore, have some sort of causal understanding of the underlying models so the tools can truly facilitate their decisions. This allows them also understand the possible limitations of these models for the manager's decision context (see e.g., Luca et al 2016). Data analytics and visualization are also changing designers' and decision makers' roles and interactions. As one manager recently told Williams et al. (2015): "My belief is always 80 percent of what an analyst gives you, you don't need or want; and 80 percent of what you want an analyst isn't going to give you".

New challenges in managing system investments relate to understanding the dynamics between the business logic-related assumptions, their system implementations, and what drives these dynamics. Investments in big data analytics primarily concern engaging large numbers of people in data-driven innovation to create exploratory and predictive business models. The growing complexity of such initiatives reduces the import of managers to understand details of underlying technologies, because they have become too complex and are constantly shifting. In addition, a large number of decisions in big data environments come with high combinatorial complexity, which makes it difficult, if not impossible (and unnecessary), for managers to understand all analyses fully. Many of these processes are also routinized. The dynamic and deeply embedded nature of the decisions in these processes make it especially difficult for managers to decipher them. Consider, for example, a manager of a large call center that automatically reallocates phone banks to service agents based on changing call volume and mix. Managers may not understand the models behind the reallocations, but they can use big data to evaluate the relative efficiency of such models and rules. Similarly, Heathrow Airport now uses a collaborative decision system that deploys dynamic decision rules to coordinate flight operations including gate assignment, refueling, flight crews, scheduling, and so on (Davenport, 2014). The system uses multiple models to make hundreds of decisions in real time from the available flight and crew data. No manager would ever have all the capability to understand how the system formulated these models and how it arrived at a solution given the disparate and voluminous data that the system gains from complex airport operations through sensors and people input. However, most managers should be able to recognize the system's diagnostic power, the general inputs that go into the diagnosis, and have the flexibility to revise their thinking.

In sum, controlling, particularly in big data and analytical environments, is more about the efficacy of outcomes and the discovery of related generative mechanisms. It is less about knowing the technical and algorithmic details of the process. Managers need to be able to engage in and assess outcomes of big data analytics and then ask hard questions related to assumptions and implied business logic (Luca et al., 2016). Doing so leads to a product view of analytics in which one needs to evaluate the outcome's (option) value. For instance, predication competitions can now use the crowdsourcing application Kaggle (Kaggle, 2015) where companies just provide the data and the "crowd" comes up with the models and interpretation. Similarly, Netflix has offered a million dollar prize in an open competition for anyone who suggests an algorithm that predicts better user ratings for films and beats Netflix' predictions by 10 percent.

Tenets of the more contemporary view include:

1. **Increased system complexity changes the dynamics between business logic and the systems as understood by the manager.**

Managers cannot transfer the responsibility of understanding the business logic to designers who neither have the managerial competence nor responsibility. However, managers need to sense and respond to business opportunities expediently. Associated decision making requires managers to have skills to quickly hone to business rules and logic that works without necessarily investing too much time on why it works at the system level.

2. **Use generalized models of crowdsourcing and correlations**.

Past control decisions assumed exact definitions of system components and their connections that would generate the system's functionality that the manager was expected to use. Often, managers needed to understand the preferred business logic being implemented in the system. However, big data implementations differ from those in the past: they deal with amplifying the discovery of generalized patterns in the data pools and how to validate the patterns using a multitude of inferential analytics and visualization tools. As such, such systems call for assimilating and deploying generic concepts of analytic modeling and different forms of visualizing business data as to discover correlations and patterns that will drive the next round of decision making. The outcome and its utility are more important than knowledge of the details of the tools used to derive them.

3. **Causal business logic trumps attempts to decipher combinatorial complexity emerging from data analytics**.

In cases where decision models and rules leverage data to automate decisions in business processes, deciphering the algorithmic complexity during the formulation and knowing the details of the computational level are unnecessary and even counterproductive. However, understanding the causal logic and its validity (i.e., what influences what) is highly useful to affect appropriate change in related systems.

4. **Data analytics is as much a product as a process.**

Managers need to be able to understand how to assess analytical outcomes and the value created. Correspondingly, one can sell analytics as a product[6] or alternatively build them into business processes as capabilities.

2 Revisiting Ackoff's (1967) Design Assumptions

In this section, we summarize our arguments about Ackoff's five original design assumptions and theses. In Table 1, we show how we have revised all of the original assumptions. The table also shows that the dominant forms of (effective) organizational decision making are being changed as the effects of pervasive analytic power that follows wide-spread computerization have become commonplace. We have changed and replaced the first assumption with another refined assumption that emphasizes discovering meaning in the new environment. We have also changed and replaced the second assumption to describe how managers can improve the likelihood of finding new relevant information through data-centric processes. The basics of the third assumption have remained the same: information alone will not improve decision making. However, we note that the process of discovering, creating, and validating decision rules has expanded and changed in substance since Ackoff's (1967) time, and the scale and need for adaptive learning now differs. Similarly, as per the fourth assumption, organizational structures and incentives still influence whether and how organizations share and use data. We note, however, that conditions of sharing and using have become more complicated and dynamic and that situations where data sharing creates opportunities for innovation exist more widely. Finally, in the fifth assumption, understanding and controlling how systems work remains managers' responsibility. However, rather than understanding complex *models*, the manager needs to control the system by being able to dynamically assess connection between the business logic and the data.

One can partly attribute these changes to the differences in hardware and software economics. At Ackoff's (1967) time, economics dictated the need for "small data". For example, the system that Ackoff mentioned as costing US$2,000,000 probably would now cost at most US$2000. Accordingly, it was important for Ackoff to focus on understanding and structuring managerial decisions to get just the "right" data for the manager's bounded unit. Without the constraints associated with data cost, connectivity, and transferability, one can now apply data to guide and inform broader organizational processes. Automating decisions based on multiple complicated data conditions (now called event-based processing; Event-processing, 2015) has opened an environment of big data and related analytics. Now, managers can cast a wide net to capture data and engage in complex analytics to cope with not only known unstructured decisions but also uninvestigated ones. They can promote real-time experimentation and business change. They can also promote the widespread sharing of data and analytics by leveraging big data's modularity.

3 Discussion

Based on the new theses and related tenets we describe above, we next synthesize five distinct but related logics that operate in contemporary data-replete environments. These logics are emerging, and we posit that they underlie the shifts we observe in Ackoff's (1967) five assumptions. We call these the logics of abduction, data layering, augmentation, active experimentation, and productization (see Table 2). As Table 2 shows, the five logics reflect and synthesize the core ideas in the tenets. Collectively, the five logics frame the new context of managerial decision making, and make it substantially different from that faced and analyzed by Ackoff. We next discuss each logic separately and then review how each influences managerial decision making of today.

[6] LinkedIn is a great example of a company that has voluminous data on its 400 million-odd members that it can monetize by offering tremendous value to advertisers, members, recruiters, etc.

Table 1. Key Assumptions and Tenets of Today's IS Environment

Ackoff's (1967) assumptions revisited		
Ackoff's (1967) core assumptions (counter-myths)	**Contemporary view**	**Key tenets**
Not filtering	**But discovery**	
1. The critical deficiency under which most managers operate is the overabundance of irrelevant information.	The critical deficiency under which most managers operate today is the growing inability to discover new relevant information from the mass of seemingly irrelevant information.	• Seek to make irrelevant data relevant. • Combine flexibly analytics, visualization, and critical thinking. • Use a broad in contrast to a narrow net for data. • Recognize and overcome bias in data.
Not deductive models	**But analytical processes**	
2. For managers to know what information they needs, they must be aware of each type of decision they make and they must create an adequate model of each.	Managers need to gather all information they can in order to discover what they truly need in emerging decision situations.	• Widen the distance between data capture and data use. • Diversify the analytical talent of managers. • Make Information needs actionable using intervention, experimentation, and external sources.
Not only judgment	**But adaptive learning through data**	
3. In most management problems, there are too many possibilities to expect experience, judgment, or intuition to provide good solution guesses, even with perfect information.	Ackoff's thesis 3 still holds. However, fast feedback, and new forms of discovering decision rules improve decision making at a different scale.	• Big data analytics offers new ways to learn from and improve past decisions. • Move constantly the tradeoff between judgment (the highest paid person's opinion (HIPPO)) and analytics toward analytics. • Simple big data analysis on complex problems can substitute (not complement) for judgment.
Not simply sharing due to structure	**But stratified data sharing depending on context**	
4. Better communication between managers does not improve organizational performance when organizational structure is taken into account.	Sharing information and analytics across functions and outside the organization, even when performance measures are in conflict, changes the dynamics and scope of organizational communications. By being shared, the data is likely to lead to joint problem formulation and decisions.	• Structure decision processes in dynamic and process-oriented way offering a context for joint data sharing. • Build on prevalent coopetition. • Promote micro-coordination based on real-time information. • Share information to generate common analytics frameworks and metrics.
Not programming or model logic	**But data inputs and outputs and causal (business) logic and related assumptions**	
5. No MIS should ever be installed unless the managers for whom it is intended are trained to evaluate and, hence, control it rather than be controlled by it.	Managers cannot understand how the system works anymore, but they need to know how to make it work in their business domain.	• Increased system complexity changes the dynamics between business logic and the systems as understood by the manager. • Causal business logic trumps attempts to decipher combinatorial complexity emerging from data analytics. • Use generalized models of crowdsourcing and correlations. • Data analytics is as much a product as a process.

Table 2. Tenets and Logic of the Contemporary Environment

Tenets	Logic of				
	Abduction	**Data layering**	**Augmentation**	**Active experimentation**	**Productization**
Assumption 1: discovery					
Seek to make irrelevant data relevant	x			x	
Combine flexibly analytics, visualization, and critical thinking		x			
Use a broad in contrast to a narrow net for data		x			x
Recognize and overcome bias in data		x		X	
Assumption 2: analytical processes					
Widen the distance between data capture and data use	x		x		
Diversify the analytical talent of managers			x		
Make information needs actionable using intervention, experimentation, and external sources				x	
Assumption 3: adaptive learning through data					
Big data analytics offers new ways to learn from and improve past decisions	x			x	
Move constantly the tradeoff between judgment (the highest paid person's opinion (HIPPO)) and analytics toward analytics			x		
Simple big data analysis on complex problems can substitute (not complement) for judgment	x	x			
Assumption 4: stratified data sharing					
Structure decision processes in dynamic and process-oriented way offering a context for joint data sharing.				x	
Build on prevalent coopetition		x			
Promote micro-coordination based on real-time information				x	
Share information to generate common analytics frameworks and metrics			x		
Assumption 5: inputs, outputs, and causal business logic					
Increased system complexity changes the dynamics between business logic and the systems as understood by the manager.				x	
Causal business logic trumps attempts to decipher combinatorial complexity emerging from data analytics	x				
Use generalized models of crowdsourcing and correlations	x		x		x
Data analytics is as much a product as a process					x

The **logic of abduction** entails that, in making decisions, managers can infer the most logical reasoning behind the data and associated postulates of local causality. They can then fine tune and test this reasoning with data. In Ackoff's (1967) time, the dominant ideal was to model generalized decisions and causal connections between decision elements founded on a Cartesian principle. By attacking increasingly complex decision problems through analytic modeling, this principle constantly moved the borderline between structured and unstructured decisions, which ultimately enhanced decision automation. As a result, many structured and common decision processes that middle or even more senior managers handled in Ackoff's time have now been automated and embedded in business processes. Now, companies face highly competitive and rapidly changing environments that one cannot easily attack with Cartesian principles. Therefore, dynamic and unstructured decisions have grown in incidence, and Cartesian deductive logic does not drive true managerial decisions as much as it used to (i.e., decision situations→models→data→ improved decisions) as Ackoff's original argument assumes. Rather, an inductive and abductive iterative logic (i.e., data→plausible reason→models→data→improved decision→data) has replaced it. As the power of machine intelligence has grown, organizations have increasingly begun to automate or crowdsource abductive logic applied on big data sets. Managers rely increasingly on this logic to discover insights for strategic and tactical decisions that are not pre-defined and amenable for analytic inquiry but emerge from the data. This logic also forms the basis for exploring the relevance of data because learning and refinement of decisions occurs through the process.

The **logic of data layering** suggests that data analytics process is expected to organize data in connectable layers that can be either distal or proximal to the problem domain. Each layer provides options for valuation of other layers. Examples of such layers include enterprise-wide system layers, customer data and interaction layers, external data layers, public data layers, and so on. Ackoff (1967) lived in an environment that was constrained by the scarcity of storage capacity and technical barriers in integrating systems; today's environment has largely alleviated these constraints. No longer does one need to collect "right" data to make a decision. In contrast, with abundant storage and the flexible digitization of transactions, behaviors, states, and communications, diverse sources, and formats, organizations can now store, integrate, and analyze data in multiple, imaginative, ways. The yield on this process depends on which data one sources, how one analyzes it, and at what speed it is done. Data layering suggests that every piece of data compiled at an infinitesimal price could potentially yield a substantial return when combined with other data at an opportune time. Therefore, it is in the interest of organizations to capture more data and cast a wider net since one cannot easily determine such yields a priori. Furthermore, simple analyses of huge data sets can yield stable and reliable insights. Unlike Ackoff's era where one matched functional tasks and decisions with specific systems, one can now constantly reconfigure and arrange decisions, data, tasks, and system functionalities in some type of "loose coupling". Decisions are largely driven by fleeting and broader strategic and tactical issues that organizations and decision makers face. Therefore, understanding data layering and exploring its option value through social media and other expertise becomes an important asset for intelligently exploring data sets. Data layers, however, are not "neutral" in their scope and nature. Companies can make decisions on what they share and keep proprietary. Here, one needs to consider issues of security, data privacy, and related regulation (Culnan & Armstrong, 1999; Schwaig, Grover, Segars, & Fiedler, 2013). Also, data introduces biases into organizational decision making by directing it. Ultimately, in this environment, digital data is a fundamental foundation for organizational decision making; it drives and shapes most facets of organizational decisions, which starts with identifying problems and issues and ends with monitoring and assessing performance.

The **logic of augmentation** suggests that data analytics and human intelligence collectively can yield better outcomes than either alone. In Ackoff's (1967) environment, the utopian goal involved substituting automated decision models for human decision making and creating an automated enterprise. Today, while complex decision rules are increasingly embedded into business processes, the logic of augmentation has become truly critical for leveraging the big data environment. At both ends of data abduction, human creativity and the corresponding social/organizational structures will determine how to identify, configure, and analyze data and how to interpret and implement emerging patterns. Overall, we face the challenge of improving the joint performance of complex data-driven analysis and decision systems that interact with systems of human actors such as designers and decision makers. Like chess where those players augmented with powerful computer tools achieve the best performance and where one can no longer separate these two components (i.e., best performance and powerful computer tools), we need to understand the joint performance of "posthuman" systems that combine artificial and natural intelligence. While Ackoff focused largely on a singular decision maker and that individual's information needs, we need to replace the individual focus with a team and with a process focus where dialogue and exchange and analysis of data between actors' influences decision making.

The organization needs to have a level of consistency in analytics talent and foster a common language and culture to create efficient human interfaces with data.

The **logic of active experimentation** indicates engagement with data that allows one to assign treatment and control groups to facilitate continuous learning, optimization of processes and launch new technology initiatives. One can perform data experiments at low cost (and low risk) by manipulating changes (e.g., on a website) and observing outcomes. This process eliminates the confusion between correlation and causality by allowing one to directly observe causes and effects. While processes lacked the visibility and integration to allow one to do experiments in Ackoff's (1967) day, today's pervasiveness and connectivity creates a sensitivity network of data that provides a fertile platform of experimentation. Managers can understand business causes and effects by playing with data in a dynamic environment that demands organizational agility.

Finally, the **logic of productization** indicates that one can increasingly manage big data analytics as an output and assess it based on its value proposition. While Ackoff (1967) primarily focused on understanding the internal model (process) of decision making, today's decision-makers primarily focus on experimenting with products' value (or option value). Also, one can outsource or crowdsource analytics and predictive modeling and can construct data architectures accordingly. The current focus on big data and heterogeneous and dynamic data sets suggests that data layers are also becoming separated from the rule layer that governs the acquisition and deployment of data in business processes. The rules have now been extensively abstracted into ERP or CRM systems and the like. Similarly, the cloud is abstracting access to data and from its "raw" computational analysis. Also, access to big data and related analytics is finally abstracting the analytic tools and related processes associated with organizational decision making into a separate dimension that one can flexibly integrate with the rules and cloud storage. Turning data analytics into products—its productization—is likely to influence how managers can integrate all these products together to enable problem discovery and new solutions in their decisions.

Overall, we can contrast the five logics that characterize the decision environment today with Ackoff's model-driven "small-data" environment (Figure 1). The new environment calls for investigating decision analysis shaped by complexity, dynamics, abduction, a systemic and emergent nature, and temporal effects.

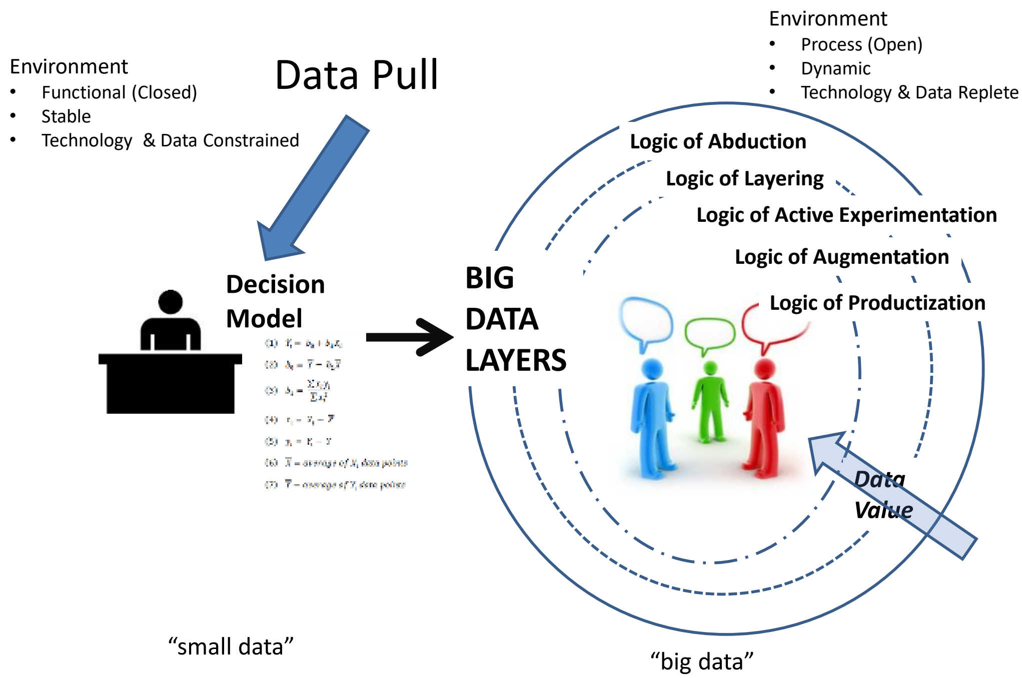

Figure 1. From Ackoff to Today

4 Pragmatic Insights

The new logics of decision making outlined in Figure 1 are clearly inter-related. They offer some practical guidance for organizations as they cope with the contemporary big data environment:

- **Active engagement** with data across layers helps separate relevant from irrelevant information and relates to logic of experimentation, layering, and augmentation. To do so, managers need to be fully engaged in the discovery process through analytics. Passive data management will result in drawing on traditional “convenience” samples and failure to execute the value option. This may result in the use of biased data in decision making, which hinders one from making good decisions in a highly dynamic and hypercompetitive environment.
- **Openness to data options and creating an analytic mindset** are critical in determining what a manager “truly” needs. Predetermined decisions can be programmed, but open, emergent and innovative decisions that now deeply affect corporate value creation must be abductive and involve active data explorations.
- **Mechanisms that facilitate trusting data and its backing over personal judgment** improves decision making effectiveness. Again, this calls for active experimentation, augmentation, and manager’s understanding how data is layered. Unlike in Ackoff’s (1967) world, managers today do not need to think in terms of optimization but rather in terms of how to use data to add value by conducting rapid experiments to assess related data value options. This builds trust over time in data.
- **Opening data for sharing** increases efficiency and innovation. Internal conflicts that come along with functional systems or organizational silos might limit how organizations can substitute superordinate goals for parochial goals. By evaluating organizational tradeoffs of data sharing across at different levels and decision contexts, the value generated through cooperation vs. competition can be better optimized.
- **Outcome and product orientation** is necessary to use data analytics effectively. While traditional environments focused on structuring and modeling decisions to drive data needs, data analytics—abstracted capabilities that one can package and leveraged either internally or externally—are important drivers of today’s environments.

5 Conclusions

For 50 years, Ackoff’s (1967) work has influenced several generations of IS scholars by shaping their views of decisions, data, and system design. In this paper, we revisit Ackoff’s original treatment in today’s environment that is technologically, organizationally, and businesswise radically different from that of the mid-1960s. We reassess Ackoff’s five assumptions and corresponding theses in light of today’s environmental characteristics that include an abundance of data and orders of magnitude difference in computing power and cost. We find that Ackoff’s theses have to some extent held the challenge of time, but that one needs to re-contextualize them to today’s world given the rapid advances in technologies of organizational decision making. We also note that vestiges of Ackoff’s work clearly remain. Most of our conventional systems-analysis approaches still rely on how to model decision processes and then determine information requirements based on what managers need. The benefits of this view are, however, mostly manifested in the increasing levels of automated operational decision making. We also note that the bigger challenge in future is to handle emerging decision situations that benefit and rely on diverse data sets and expertise and rely on “big” data analytics. To do well in these tasks, managers need to increasingly honor the power of evidence and its analytic backing and put it before personal judgment, develop new types of analytic mindsets and engage actively with data, and use analytic technologies to augment their intelligence. To do so, managers need to more deeply investigate the tensions and challenges of integrating analytic procedures with varying domain expertise, intuition, lateral thinking, and managers’ emotions—topics we don’t cover here because they fall outside the scope of Ackoff’s original argument .

While our analysis remains relatively abstract, we surmise that it can serve to frame a broader IS research agenda for decision making in the new environment. One element in this process involves critically evaluating prevailing assumptions about organizational decision making and how they inform our inquiries into information system design and use. We need to critically evaluate how we approach and think about data, its provenance, privacy, and related organizational practices. We need to subject such aspects to much more careful analysis and theorizing. For example, we need ask how now data is dependent on and informs organizational action in specific domains, how the costs and benefits of data are evaluated, and how related economic decisions are carried out.

One could also study the logics we articulate in this paper in more depth. The logic of abduction is at the core of data mining but has not been studied extensively. On this topic, studies that have been carried out about sense making and abduction using data sets in scientific inquiries can be one source of inspiration. We also need research that examines how management interfaces with both the front and back end of the data-driven decision processes. The logic of layering raises interesting questions about estimating the option value of data and how one can combine various types of data to create novel value. The logic of augmentation deals with broader issues of combining data (computing) and human skills to augment value, which have not been extensively approached from the view point of complementarities and underlie much of the original theory of socio-technical (purposeful) systems also put forward by Ackoff and his colleagues. Delineating the antecedents and moderators of effective augmentation offers a rich topic for research. The logic of active experimentation indicates how managers can hone their initiatives dynamically through causal mapping. The logic of productization raises questions about the architecting and modularity of big data and related analytics and when one can outsource it to benefit from crowdsourcing.

Overall, we need to articulate more refined technology-imbued theories of data origination, use, management, and control. One may apply these theories not only at the organizational level but also at the level of business processes and industries. Consider, for example, the data-intensification and automation effects in financial services and the new emerging forms of financial technologies and related investments (Economist 2015). We also need better models and theories of decision making that go beyond individual decision makers and analyze teams and communities that constitute complex socio-technical “posthuman” systems of decision making. Finally, we need to better understand the conditions and effects of extensive data sharing, micro-coordination, and how it influences the allocation of decision processes and rights, managerial cognition, and innovative outcomes.

What particularly excites us in this exercise is that, while reevaluating Ackoff’s (1967) work, we could acknowledge the significance of his work and legacy. By doing so, we sensed tremendous opportunities for the IS field to reinvigorate its study of managerial decision making in the current exciting and rapidly changing environment by continuing to revisit the same questions we started to ask about 50 years ago.

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About the Authors

Kalle Lyytinen (PhD, Computer Science, University of Jyväskylä; Dr. h.c. Umeå University, Honorary Doctorate, Copenhagen Business school) is Iris S. Wolstein professor of Management Design at Case Western Reserve University and a visiting professor at Aalto University, Finland. Between 1992 and 2016, he was the 3rd most productive scholar in the IS field when measured by the AIS basket of eight journals; he is the LEO Award recipient (2013), AIS fellow (2004), and the former chair of IFIP WG 8.2. He has published over 300 refereed papers and edited or written nearly 20 books or special issues on the nature of IS discipline and theories, computer supported cooperative work, standardization, ubiquitous computing, social networks, organizational change and process theorizing, and digital innovation. He recently edited a special issue in *MISQ* on digitally enabled innovation and is involved in research that explores digital innovation especially in relation to design work, requirements in large scale systems, and the evolution of digital infrastructures.

Varun Grover (PhD, IS, University of Pittsburgh) is the William S. Lee (Duke Energy) Distinguished Professor of Information Systems at Clemson University. He will be taking a position as the David D. Glass Chair and Distinguished Professor in Information Systems at the Walton College of Business, University of Arkansas. He has published extensively in the information systems field, with over 220 publications in major refereed journals. From 1990-2016, he is ranked second in research productivity based on publications in the AIS basket of six journals and has an h-index of 78 and over 27,000 citations in Google Scholar. Thompson Reuters recognized him as a highly-cited researcher in 2013. He is Senior Editor for *MISQ Executive*, Editor of the *JAIS* section on breakthrough research, and Senior Editor (Emeritus) for *MIS Quarterly*, the *Journal of the AIS,* and *Database*. He is currently examining the impacts of digitalization on individuals and organizations. He is recipient of numerous awards from USC, Clemson, AIS, DSI, Anbar, PriceWaterhouse, and so on for his research and teaching and is a Fellow of the Association for Information Systems.