Bridging the data divide between practitioners and academics: Approaches to collaborating better to leverage each other's resources

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ABSTRACT

Purpose: Organizations (data gatherers in our context) drown in data while at the same time seeking managerially relevant insights. Academics (data hunters) have to deal with decreasing respondent participation and escalating costs of data collection while at the same time seeking to increase the managerial relevance of their research. We provide a framework on which managers and academics can collaborate better to leverage each other's resources.

Design/methodology/approach: This research synthesizes the academic and managerial literature on the realities and priorities of practitioners and academics with regard to data. Based on the literature, reflections from the world's leading service research centers, and the authors' own experiences, we develop recommendations on how to collaborate in research.

Findings: Four dimensions of different data realities and priorities were identified: research problem, research resources, research process, and research outcome. In total, 26 recommendations are presented that aim to equip academics to leverage the potential of corporate data for research purposes and to help managers to leverage research results for their business.

Research limitations/implications: This article argues that both practitioners and academics have a lot to gain from collaborating by exchanging corporate data for scientific approaches and insights. However, the gap between different realities and priorities needs to be bridged when doing so. The article first identifies data realities and priorities and then develops recommendations on how to best collaborate given these differences.

Practical implications: This research has the potential to contribute to managerial practice by informing academics on how to better collaborate with the managerial world and thereby facilitate collaboration and the dissemination of academic research for the benefit of both parties.

Originality/value: Whereas previous literature has primarily examined practitioner–academic collaboration in general, this study is the first to focus specifically on the aspects related to sharing corporate data and to elaborate on academic and corporate objectives with regard to data and insights.

INTRODUCTION

In every minute of every day, around half a million tweets are sent, over four million videos are watched on YouTube, and 120 new professionals join LinkedIn (Marr, 2018). We created 2.5 quintillion bytes of data per day in 2017 and, up until then, 90 percent of the world's existing data had been generated in the years from 2015 to 2017 (IBM Marketing Cloud, 2017). In addition, there is an increase in firms collecting biometric data via, for example, Fitbits, which logged 150 billion hours of heart data from tens of millions of people across the globe (Becker's Hospital Review, 2018). With the rapid deployment of geotagging, censors, artificial intelligence (AI), the Internet of Things (IoT), and platforms that capture every movement of their stakeholders (Wirtz et al., 2018; 2019), the amount of available data generation is set to continue accelerating.

Every interaction with a customer, whether that be sales transactions or customers contacting a helpline, complaining, or filling out a customer survey, creates data points (Kumar et al., 2013; Moe and Ratchford, 2018). Such data, whether raw or refined to give knowledge and insights, can be relevant for service research. With customers engaging with brands online, available data goes far beyond company-managed interactions (Blazevic et al., 2013; Wirtz and Tomlin, 2000). It is not surprising, therefore, that organizations use less than one percent of their unstructured data (e.g., text, voice, images, observed behaviors on websites and in apps, and IoT-generated data) in any way, and even for structured data (i.e., numbers in a format that would allow analysis), less than half is used for decision making (DalleMule and Davenport, 2017). This leads us to portray companies as data gatherers, accumulating increasing amounts of data with often limited usage of it.

At the same time, researchers spend enormous amounts of time, effort, and financial resources to collect (primary) data by conducting interviews, focus groups, experiments, and surveys, as academic journals and their editors seem to favor empirical over conceptual work

(Benoit et al., 2017; MacInnis, 2011; Yadav, 2010). With the exception of convenience samples (e.g., students or MTurkers), the required effort needed to gather such high-quality primary data has grown over the years, since it is increasingly difficult to secure participation (aka responses) for empirical research (Baruch and Holtom, 2008; Shaw, Bendall and Hall 2002). This leads us to portray researchers as *data hunters* who require an increasing amount of effort to collect data for their research, while at the same time experiencing an increasing need to do so in order to get published.

Much has been written about the disconnect between the academic and the managerial worlds. The existing literature has produced a stream of research regretting (e.g., Amabile et al., 2001; Anderson et al., 2001; Markides, 2007), elaborating on (e.g., Aram and Salipante, 2003) and investigating the drivers and the background of this disconnect (Birkinshaw et al., 2016; Hambrick, 2007). The identified reasons include a different understanding of what constitutes managerial relevance (Nicolai et al., 2011), different priorities (Amabile et al., 2001), costs associated with generating knowledge (Anderson et al., 2001), communication practices, and time horizons (Bartunek and Rynes, 2014).

Given the above, it is not surprising that research exists on how to overcome the disconnect. The existing research suggests shifting methods towards more action research and qualitative methods involving practitioners (Avenier and Cajaiba, 2012); communicating more often and better, including learning each other's languages (Amabile et al., 2001; Barrett and Oborn, 2018); publishing in bridging media such as the Harvard Business Review (Birkinshaw et al., 2016); and lobbying governments and policy makers to require practitioner involvement in government-funded projects (Anderson et al., 2001). These are valuable solutions, but there is still a lack of guidance as to how to collaborate in ways that leverage each other's resources (Bansal et al., 2012; Bartunek and Rynes, 2014).

The working assumption of this article is that academics and practitioners alike have a

lot to gain from research collaboration (e.g., Amabile et al., 2001), including the provision of data (from the managerial world) against insights (from the academic world). This article develops recommendations on how to leverage each other's data and data analysis capabilities.

To address these aims, we first investigate the data realities and priorities: i.e., more data accumulation with less ability to process it in the managerial world, and less availability of data with more effort required to gather it in the academic world (Table 1). This enhanced understanding serves the purpose of building a framework of recommendations as to how to fruitfully collaborate given these priorities (Table 2). This framework is based on a literature review, the experiences of the authors (who have regularly and successfully collaborated with the managerial world), and reflections from members of some of the world's leading service centers.

THE DATA DIVIDE: MANAGERS' DATA AND ACADEMICS' INSIGHTS

Generating data as such is not the problem; vast amounts of it is created every second by millions of people. Data generation will accelerate further with the deployment of the IoT, which turns analog goods into digital goods. What troubles practitioners in this day and age is not getting their hands on enough data, but making smart use of the existing data and generating insights from this data (Kumar et al., 2013). This is where academics can play an important role: They take time to dig deep, examine patterns, identify structure – in short, they can, using AI and machine learning, turn data into managerially and scientifically relevant insights to be used for decision making, optimization, predictions, and innovations.

Data, however, differ according to who collected it and when. Specifically, customers frequently "interact with firms through myriad touchpoints in multiple channels and media, and customer experiences are more social in nature" (Lemon and Verhoef 2016, p. 69).

Figure 1: Big data and the customer journey

	Customer Journey		
	Pre-encouter stage / service facilities	Service encounter stage	Post-encounter stage
Volume	Brand-owned Touchpoints		
	Partner-owned Touchpoints		
Velocity	Customer-owned Touchpoints		
Variety	Social/external-owned Touchpoints		

(Left vertical label: Big Data)

Firstly, data can be identified as passing through different phases during the customer journey. In accordance with previous research, and to make the process more manageable, customers integrating their resources into a firm's processes can be conceptualized into three phases (Moeller 2008; Tsiotsou and Wirtz 2015): (1) the pre-encounter stage or service facilities, which encompasses every aspect of consumer–brand interactions that happens before the customer is integrated into the service process, including need awareness, information search, evaluation of alternatives, and decision making; (2) the service encounter or transformation stage, which covers all interactions during the service encounter, including the entire customer journey through the consumption process, and can include self-service and interaction with websites and apps; and (3) the post-encounter stage, which encompasses benefitting from the service, evaluation of the service performance (i.e., customer satisfaction and service quality) and post-encounter behaviors such as word-of-mouth, referrals, and online brand community engagement.

Secondly, data can be distinguished at different kinds of customer touchpoints during the customer journey. Companies can gather or have available a lot of data regarding customer interactions with "brand-owned touchpoints" (Lemon and Verhoef, 2016). During

all stages of the customer journey, companies have control of these touchpoints, such as company websites, apps, company-controlled IoTs, hosted groups, own stores, marketing mix activities, and customer support and service. In many cases, companies rely on partners (e.g., retail, logistic, and maintenance service partners) to create wholesome customer journeys and experiences. This might lead to jointly controlled touchpoints such as multivendor loyalty programs, sales partners (especially in the B2B environment), affiliate programs, or simply agreed access to data from these sources. In these cases, companies have to surrender control of and influence on their customers' experiences as well as data sovereignty, but also have to integrate data from external sources such as partner- and even ecosystem-owned touchpoints. This makes data sharing difficult, as companies have no, or only limited, control of these socially and externally owned touchpoints (Lemon and Verhoef, 2016; Moeller 2008). Furthermore, these exchanges often occur on social media and hence consist of mainly unstructured data such as text, images, and videos.

Thirdly, data can be differentiated based on the 3V model (i.e., volume, velocity, and variety) of big data (Bhadani and Jothimani, 2016; Gandomi and Haider, 2015). *Volume* refers to the sheer amount of data generated, often via electronically supported business processes as described above. *Velocity* describes the rapid pace with which our social and economic transactions are digitally captured (Agarwal and Dhar, 2014) leading to terms such as data explosion (Kumar et al., 2013; Moe and Ratchford, 2018). *Variety* refers to data in the managerial world varying from structured through semi-structured to unstructured data (Gandomi and Haider, 2015). Along the customer journey, managers are faced with sales figures, typical shopping baskets, buying patterns on- and offline, customer feedback via service channels, and discussions on social media networks. Although the information is available, managers seem to find it hard to convert data into actionable insights (Kumar et al., 2013). With all this data at hand, the challenge of managers thus shifts from solving

predefined problems by extracting the right answers to identifying the right questions (Dhar, 2013). This challenge requires different methods of inquiry for dealing with the data, as will be discussed later.

Given the rapidly increasing volume and types of data generated by digital technologies, collaboration is in both managers' and academics' interest to advance and make use of this momentum (e.g., Amabile et al., 2001). To leverage each other's resources, though, both parties have to understand the other's goals, preferences, and constraints, and understand better each other's language. The following section aims to support this by reviewing the data realities and priorities of managers and academics.

DATA REALITIES AND PRIORITIES OF MANAGERS AND ACADEMICS

Table 1 organizes data realities and priorities into the following dimensions: research problem, research resources, research process, and research outcome (adapted from Frank and Landström, 2016).

Table 1: Data realities and priorities of practitioners and academics

Realities and priorities	Managerial world	Academic world
Research problem		
Generalizability	• A high level of context is positive; it is relevant to making managerial decisions.	• A high level of context is negative; it compromises the generalizability of results.
Specificity	• Managers have to deal with broader questions, including all exogenous factors (big picture).	• Academics are highly specialized in their area of expertise and often try to cancel out exogenous factors in their research (small picture).
Research resources		
Data access	• There is often more data than there is the capacity to process it. • There is often a lack of ability to convert data into actionable insights.	• Data are a scarce, increasingly important resource. • Primary data collection is increasingly difficult, but at the same time urgently needed.
Data recency	• Recent data are critical for contextualized questions where context changes frequently. • Data are "too old" after a couple of months.	• Recency of data is less relevant as they are used for more abstract, less context-dependent questions. • Data are "too old" after a couple of years.
Data sharing	• There is a fear that sharing does not comply with data protection laws. • It takes operational effort for providing data access; e.g., the costs involved in retrieving it.	• Personal, confidential data are usually not needed; anonymized data are sufficient. • There is frequent unawareness of the effort required in working with enterprise-type databases.
Research process		
Generalists vs specialists	• CEOs and senior managers tend to be generalists with strong leadership (as opposed to technical) skills.	• Academic researchers tend to be highly specialized (topics, theories, and methods).
Communication styles	• CEOs and senior managers tend to be good storytellers – they need straightforward messages that can be easily understood and embraced by all levels within the organization.	• Academic researchers are often poor storytellers – they are comfortable with complexity and uncertainty (and often disdainful of simplicity); in fact, they are trained to point out the limitations in their models.

Realities and priorities	Managerial world	Academic world
Approach of knowledge creation	• Induction: The starting point of an investigation is usually some observation in reality or related data that leads to a process of sense-making and development of patterns, i.e., hypotheses and theory.	• Deduction: The starting point of an investigation is usually a search for a gap in the literature, a literature review, and a theory from which hypotheses are deduced and then tested on data.
Priorities in knowledge creation	• Focus on relevance	• Focus on theory and rigor
Timing and project management	• The expectation is that data analysis takes days up to weeks, adhering to set milestones.	• The reality is that data analysis often takes months to years, often without fixed milestones.
Lack of appreciation of effort required to provide data	• Managers often assign a low priority to academic efforts because of (1) the time demands necessary to perform their required job functions, and (2) a lack of clear rewards for the extra time commitment required.	• Researchers tend to underappreciate the effort required for managers to compile and provide the desired data and therefore ask for much more than necessary, and in formats that are not readily available.
Research outcome		
Sharing results	• There is a fear that publishing results might compromise the firm's competitive position.	• Academic publications tend to be too abstract and take too long to be able to compromise a competitive position. However, academics are keen to present initial results at academic conferences to obtain feedback.

Research problem

Generalizability. Practitioners and academics often have different priorities with regard to the extent of the applicability of research to various contexts: that is, the generalizability of the research (Bansal et al., 2012; Van de Ven, 2018). Very context-specific research is applicable only to certain circumstances or situations (Belk, 1974). For example, a manager from a local car-sharing company planning to change the pricing model is interested in whether his customers would prefer the new pricing model, e.g., a subscription-based one. In contrast, academics seldom care about a certain context, industry, or country (Van de Ven,

2018). In fact, a very specific context is usually a liability because of its relevance to a
limited target group (Nobel, 2016), and because it also becomes outdated quickly (Walsh et
al., 2007).

Practitioners are particularly interested in solving their organizations' pressing
problems, while academic research aims at developing general knowledge that holds beyond
an empirical context (Avenier and Cajaiba, 2012; Busse et al., 2017). However, academics
can test their theoretical assumptions in multiple contexts and draw learning from that. It can
be helpful to managers to consider not only the corporation itself but also the more general
picture. They could see the academic as a consultant who provides knowledge applicable to
their context, whereas the academic might be willing to do so in exchange for (contextual)
data or access to other resources (Amabile et al., 2001; Van de Ven, 2018). Furthermore, for
academics to be managerially relevant, research needs to relate to some context (Dellaert et
al., 2008).

Specificity. Academics often build theoretical models and set up (e.g.) experiments that
leave out the so-called "exogenous factors" in order to focus on a very specific question
(small picture). Models would otherwise be far too complex, or causality might be
confounded (Bennis and O'Toole, 2005). Whereas generalizability refers to the ability of the
research to predict behavior outside of the study situation, specificity refers to the scope of
the subject area (Goldsmith et al., 1995). Small-picture, highly generalizable research would
thus look at a very narrow question (e.g., consumers' perception of price-matching
guarantees) for which the results are applicable to all situations that show this characteristic
(all offerings with a price-matching guarantee). However, this research blends out any other
(pricing-related) questions or issues. Often, big-picture "multifaceted questions do not easily
lend themselves to scientific experiment or validation" (Bennis and O'Toole, 2005, p. 99).
However, in practice, blending out other, "exogenous" factors is not possible.

Research resources

*Data access***.** In the managerial world, data are often a by-product of ongoing organizational (e.g., sales, social media marketing, and customer service) and customer activities (e.g., interactions with the organization's websites, apps, and platforms). Because these activities are supported by technology, e.g., 5G and IoT, data emerges and grows automatically – often at an exponential pace, capturing various customer touchpoints. The Internet has enabled academics to scrape large amounts of unstructured data such as customer feedback that is left online (see e.g., a study on Amazon reviews by Ludwig et al., 2013) as well as to conduct large-scale consumer experiments and surveys on social phenomena at low cost (Agarwal and Dhar, 2014; Dhar, 2013). Laboratory experiments are not a safe haven, though, as they are often criticized for their unrealistic environment, and they are limited in their scope to some areas of research (such as B2C marketing research). When conducting research on B2B or organizational topics, securing managers' participation has become increasingly difficult due to eroding response rates year by year (Baruch and Holtom, 2008; Shaw, Bendall and Hall, 2002). As a result, academics often spend a lot of effort and financial resources collecting primary data. What seems to be a data overflow in the managerial world is a scarce and valuable resource for academics.

*Data recency***.** Practitioners' and academics' time horizons differ, with academics' timelines being much longer than those of practitioners (e.g., Bansal et al., 2012). For managers, data that is more than a couple of months, or even weeks, old is often "too old" to be of relevance because of the high contextualization of their problems and the rapid changes in their environment (Moe and Ratchford, 2018). The more abstract questions that academics tend to address do not require data as recent, and it is therefore less relevant whether these data are a couple of months, or even years, old. Academia implicitly bases its work on the assumption that on a more abstract level, change happens at a slower pace, so that systematic

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patterns identified in data that are considered to be "old" in the managerial world will still hold.

Data sharing. Companies are hesitant sharing data with anyone outside the organization because of the need to comply with legal frameworks around data protection and privacy (e.g., the GDPR in Europe: see https://eugdpr.org) as well as increased consumer sensitivity to data privacy (Kumar et al., 2013), further fueled by incidents such as the Cambridge Analytica scandal in 2016 (Janrain, 2018).

In addition, managers are concerned about the effort and costs needed to obtain the data from their IT departments. Often, managers' departments are charged by their shared service providers, including IT, for which a budget needs to be obtained. Furthermore, IT departments tend to be busy and prioritize their projects, which can make it a challenge to get a non-urgent project such as university-related study done. Finally, the data involved are frequently much larger than what fits onto a typical hard disk drive and tend to be complex, thus requiring additional work to be made usable by academics.

Research process

Generalists vs specialists. Top executives within companies are more likely to have worked in diverse areas rather than specializing in a single area (Lazear 2010; Lebowitz, 2017). As Lee, 2010 states, "The higher you get in an organization, the more likely you are to encounter problems from a variety of different areas … those people have to be generalists." By contrast, academic researchers must be highly specialized in their fields. In fact, researchers often possess expertise in a very narrow area of a specialized field of research. They must conduct research that advances the scientific body of knowledge if they are to be successful. The need to advance the field of study demands that researchers investigate under-researched rather than mainstream topics to uncover "new to the world" insights. Understandably, managers sometimes view academic research topics as too complex and too

special with limited upside potential for advancing the competitive position of their organizations. As a result, managers often reject sophisticated models that frequently come with boundary conditions and limitations that they find difficult to understand and rather "revert to models of great simplicity" (Little 2004, p. 1855).

Communication styles. Successful leaders within companies tend to have dramatically different communication styles from most academics. They must be able to compellingly convey their visions for the organization, and inspire confidence among employees within the organization that the objectives are worthwhile, attainable, and beneficial to them individually. As such, they must project confidence (often bordering on certainty). The following example highlights this need: *"In a lecture at Vanderbilt University, Roger Sawquist, former CEO of Calgene, Inc., maker of the first genetically altered food for consumer use, the Flavr Savr tomato, explained why he never wanted his company's scientists to speak to the public. To paraphrase his explanation, scientists never say that something will not happen, even if it has an infinitesimally small probability of occurring. Being scientists, virtually nothing is considered impossible, no matter how improbable. Sawquist, on the other hand, noted that when the probability is minuscule, he personally had no problem stating that such an occurrence 'absolutely would never occur!'"* (Keiningham and Vavra 2001, p. 52). And while managers certainly do not want models that are potentially wrong, "managers need to balance precision with the ability to easily understand and communicate the fundamentals of the model selected" (Keiningham et al., 2015, p. 24). The need to get everyone in the organization aligned and focused on achieving the same goal is paramount.

In contrast, academic researchers are famously precise, factual communicators. Not surprisingly, the general public often holds a stereotype of professors as inept communicators. While many researchers are much better communicators than these

stereotypes suggest, in general, academic researchers lack the polish and persuasiveness of many senior executives within companies. For example, academics are trained to point out the limitations of their findings. The end result is that academic researchers are frequently poor storytellers and lack the skill of putting findings in a business context and explaining clearly questions such as, "What does this finding mean for managers?" or "What should the firm do better?" This lack of persuasiveness hampers researchers in their ability to sway senior managers to partner with them in accomplishing their research objectives.

These different ways of communicating make it very difficult for academics to persuade managers that data sharing will support their needs. Academic researchers often think that a dispassionate logical approach is the best way to convince managers of the merits of working together. However, the inescapable reality is that virtually no decision we make is based solely on logical reasoning. The prefrontal cortex is wired to balance logic with emotion so that we can value one option over another. Without this combination, we are unable to make even the most basic of decisions (Eagleman, 2015).

Approach to knowledge creation. Practitioners mainly, but also some researchers, usually proceed with an inductive, i.e., data-driven, approach that starts with observing some phenomenon in reality, some managerial problem, or an upcoming decision, and then exploring the existing data and trying to identify reasons for the phenomenon and answers to the problem. They then develop hypotheses or theories that did not exist beforehand (Bartunek and Rynes, 2014; Briner and Denyer, 2012; McAbee et al., 2017).

In academia, the procedure for generating knowledge is mostly deductive, i.e., theory-driven, meaning that the starting point is identifying a gap in the literature, aiming to fill this gap by formulating hypotheses from existing theories and testing those with data by applying quantitative research methods. This so-called "gap-spotting research" is perceived to be one of the major drivers of the academia–practitioner gap, since this might draw academics away

from interesting phenomena emerging in the real world in favor of spotting some incremental aspects in a stream of research that has not yet been looked at (Alvesson and Sandberg, 2013). Some scholars have thus argued that there is an overemphasis on deductive approaches (McAbee et al., 2017; Hambrick, 2007) and that it can be highly valuable for generating meaningful insights to not be forced "to make assumptions about the nature of the relationship between variables before we begin our inquiry" (Dhar, 2013, p. 67). An overemphasis on theory might lead academics to disregard interesting research questions, or to fit their questions or models into a theoretical framework that leaves out the interesting aspects (McAbee et al., 2017; Hambrick, 2007).

Inductive approaches are largely condemned in academic practice, though, and are deprecatingly designated as "dustbowl empiricism" (McAbee et al., 2017), since most of us are trained to believe that research questions must originate from prior theory, whereas data are mainly used to check the validity of the theory (Dhar, 2013). The negative perception of inductive research risks neglecting opportunities in the growing amount of data that is generated today. That said, theory is valuable and not simply a straitjacket, since scholars have a competitive advantage in knowledge generation because they can rely on frameworks and theories that give guidance on where to look for the right connections in the data (Moe and Ratchford, 2018). In this regard, we agree with Hambrick (2007) that for the emergence of new theories, various forms of atheoretical or pre-theoretical work are instrumental. Today, with the speed of data generation and the means to analyze it through machine learning, academics have a multitude of possibilities to change the nature of the research process and generate interesting findings and new theories (Dhar, 2013). We suggest that editors and reviewers be open to these alternative approaches.

Priorities in knowledge creation. For research to be considered as valuable, it needs to be interesting, relevant, and rigorous (Frank and Landström, 2016), although this is often

reduced to rigor and relevance (Anderson et al., 2001; Aram and Salipante, 2003). "Interesting" research is defined as novel, creating new directions, or providing new perspectives. Relevance is defined as useful, applicable, and connected to some kind of action or task for a target group (either academics or practitioners). Finally, rigor relates to the use of theories, technical quality, sophistication, objectivity, reliability, and validity of the research (Baldridge et al., 2004; Frank and Landström, 2016).

Scholars are divided as to whether rigor and relevance are mutually exclusive or can be achieved simultaneously, or whether rigor is the condition for relevance (Baldridge et al., 2004; Vermeulen, 2005). The literature suggests that academics overemphasize rigor, whereas practitioners mainly care about relevance (Aram and Salipante, 2003; Bansal et al., 2012). Academics seem to generally feel that a push for more managerial relevance will interfere with rigor (Bartunek and Rynes, 2014). Furthermore, funding agencies such as national research councils and EU grant agencies have strict requirements that funded research must address (e.g., contribute to solving problems relevant to society, such as immigration and integration; to organizations, such as digitization and sustainability; or to consumers, such as privacy protection and improved healthcare services).

Timing and project management expectations. Priorities regarding rigor and relevance are usually accompanied by very different expectations with regard to timing and adherence to milestones. Practitioners usually require rapid responses and adequate data support for their immediate decision making (Bansal et al., 2012), and they set milestones that teams work towards. However, high-quality research should be (but usually is not) project-managed, meaning that it generally takes more time than managers typically allot to dealing with issues of concern (Bartunek and Rynes, 2014). As a result, from the perspective of managers, academic research is often outdated the moment it is published (Moe and Ratchford, 2018). One example makes this apparent: "When we got some research funding

… to explore food price volatility, it was top of our advocacy agenda, but food prices calmed down, the campaign's spotlight moved on, and the resulting research, though really interesting, struggled to connect…" (Green, 2016).

Lack of appreciation of effort required to provide data. Even if practitioners are willing to share data of various types (see Table 1), the data are generally not readily accessible, and frequently there are different data types in incompatible formats. This means that operationally, retrieving the required data in a suitable format to answer certain questions, e.g., to relate to types of variables, or to enable the application of statistical procedures, entails substantial time and effort and thus has high opportunity costs on the company side. The academic, on the other hand, likely has little transparency about the difficulties involved with retrieving the data (due to the different sources of that data), even though managers might be willing and able to help. At the same time, researchers tend to expect the data to be clean and formatted in a way that makes analysis relatively easy, which is generally not the case.

Research outcome

Sharing research results. It is regularly asserted in the literature that academics could and should be better at making their results accessible to a wider audience and "translating" them into readable pieces, e.g., in practitioner journals (Shapiro et al., 2007). However, when collaborating with an organization and gaining access to their data, this might be exactly what managers fear. Other organizations, potentially their competitors, may gain access to these insights such that potential competitive advantages gained through the research insight might be lost. From our experience, managers' awareness that at some point the research results will be publicly available increases their hesitance to even start a collaboration. They worry that results that are unknown at the time of agreement might become common knowledge after publication.

Overall, we are under no illusion that the above differences in realities and priorities will continue to exist. However, in the following section, we aim to contribute by giving recommendations for mitigating these challenges.

RECOMMENDATIONS FOR LEVERAGING DATA REALITIES AND PRIORITIES

The framework, outlining the recommendations on how to best leverage the different data realities and priorities in the managerial and academic worlds, has been developed in two steps. The initial framework was based on a literature review and the authors' personal experiences of having regularly and successfully collaborated with the managerial world, or having worked in industry. In a second step, we gathered a list of service research centers around the world from the SERVSIG website (www.servsig.org) and gathered feedback from their members. In particular, we asked for a reflection on the framework of recommendations and whether these reflected their best practices, and also whether they had any additional recommendations. Of the 15 service research centers contacted, nine provided feedback either in writing, via personal conversation, or as part of the author team (their names are listed in the acknowledgments). As such, this article integrates the extant literature and the implicit knowledge of the authors and members of some of the world's leading service research centers. The objective is to make this knowledge explicit by formulating recommendations on how academics can collaborate better with the managerial world in order to leverage data realities and priorities (see Table 2).

Table 2: Recommendations for academics on how to leverage data realities and priorities

Data realities and priorities	Recommendations
Research problem	
***Generalizability.** The high contextual level of research makes it managerially relevant.*	• **Co-develop research questions.** Research questions evolve over time, and managers can often identify problem areas but not concrete research questions. • **Frame your research in a context-specific way.** Communicate with practitioners on a context-specific level rather than on a generalized level. • **Think of 2-in-1 solutions.** Be open to including additional elements in the research design, e.g., interview questions, or items or manipulations that allow answering of specific questions that are important to managers.
***Specificity.** Managers have to deal with the big picture, and too narrow and specialized research is frequently not supportive of managerial decision making.*	• **Clarify the scope of the project.** Clarify expectations on the key objectives of the research, its scope and process, and put those in writing. Explain the differences between collaborating with academics versus consultants: Consultants are hired to work on a particular client problem, whereas researchers will likely only have a goal overlap. • **Provide practitioners with the big picture.** Make results from the literature review part of the result presentation to provide a big-picture perspective; consider your particular results as one piece of the big picture.
Research resources	
***Data access.** Often the managerial world has more data than the capacity to process it, but lacks analytical skills and actionable insights.*	• **Create a network of practitioners and engage with them.** Build your network by attending practitioner events, leverage contacts from the university, engage with guest lecturers and practitioners who react to the university's and researcher's dissemination activities, and reach out to former students. Engage practitioners in guest lectures and student projects. Do consultancy, and generally start small and do it well, as working well together builds trust. • **Choose relevant research areas.** Get inspiration from practitioners' pressing problems and make your research useful to them. Consider deducting research questions from real-world issues by skimming through practitioner journals, thought leadership pieces from leading consulting firms, industry conferences and the like. • **Sell cutting-edge research skills** that provide a competitive advantage over organizations' in-house teams and consultants. Academics have access to the latest academic literature and thinking, and they often have sophisticated methods and analytical skills.
***Data recency.** Current data are critical for managers but less so for academics, for managers data is "too old" after weeks*	• **A dataset can have many forms and shapes.** While getting a "complete" data set is preferable, it is often not necessary. In the event of barriers, it is better to only get access to a certain region, or a subset of customers or products, than no access at all. Also, if academics need data the organization views as too sensitive to share, the academics can offer to work with older data for a particular academic aspect of this joint project.

Data realities and priorities	Recommendations
rather than years.	
Data sharing. *Managers fear that data sharing does not comply with data protection laws and requires too many resources.*	• **Be aware of the legal framework.** Be prepared for what the legal framework allows in the particular country to be able to have an informed discussion about this issue, and secure approval from the organization's legal department. • **Relegate to data and privacy regulation at universities.** Clarify that universities generally have strict data protection and privacy principles and regulations, which can help in building trust. • **Emphasize that only anonymized data are needed.** Make practitioners aware that there is no need to provide personal data or data that allow identification of individuals; anonymized data is all that is needed. • **Provide sample articles to reduce barrier.** Show practitioners sample publications of research based on company data, ideally from yourself and/or with the involvement of other well-known companies in their industry to demonstrate that competitive threat and data protection issues from academic publications are generally negligible.

Research process

Generalists vs specialists. *Managers tend to be generalists and academics specialists*	• **Study your audience before interacting.** As senior managers are generalists, simpler models and synthesized updates and reports tend to work best. That is, updates and reports have to be short and to the point, and technical details moved to an appendix.
Communication styles. *Managers tend to be excellent storytellers and academics less so*	• **Try to be bilingual – speak the academic and the managerial languages.** Have a compelling story about the benefits to managers and their organizations, and the problems this project solved for them; the story should not focus on the academic research problem. Also, remove academic jargon and adapt it to managerial language. • **Create different result presentations.** Managers often think in descriptives, main effects, and problem–solution patterns, whereas academics often think in more complex models and coherences. Produce different presentations to tailor to the incompatible needs of these two audiences.
Approach to knowledge generation. *Managers tend to be inductive (observation and problem first) and academics tend to be deductive (theory first).*	• **Use inductive and deductive approaches simultaneously.** Use the strengths of both approaches. The inductive, data-driven, atheoretical and pre-theoretical approaches can be instrumental to academic progress and building the basis for new theory generation. The deductive approach combined with literature provides the guidance to test specific hypotheses for theory testing. To do this effectively, be knowledgeable about the literature and its gaps when discussing potential research questions and approaches with managers, and also be open and flexible within your area of interest.
Priorities in knowledge generation. *In general, managers focus on relevance,*	• **Prioritize relevance and rigor depending on the research stage.** Having more managerial input into what the research will investigate is likely to enhance its relevance. In contrast, how the research is conducted requires a rigorous approach to yield high-quality publications.

Data realities and priorities	Recommendations
and academics on rigor.	
Timing and project management expectations. *Managers need quick results (in days or weeks) whereas academics can take months and years.*	• **Identify project owners and set frequent and manageable milestones** to keep practitioners engaged, and set expectations about how long the different steps are likely to take. • **No urgent questions.** Avoid corporate research questions that are urgent, as most academics will not be able to deliver within expected timeframes. Rather, find research questions that are relevant and important but not urgent. These are often strategic and forward-looking questions that managers are happy to jointly explore with academics. Examples could include questions on new technologies and consumer responses. • **Present preliminary results shortly after data collection** to provide managers with the desired quick insights. The analysis can be simple and largely descriptive.
Effort required to provide data. *Managers often assign low priority and resources to projects with academics, and academics underestimate the effort required for firms to provide the desired data.*	• **Make data provision easy.** Offer time and help with retrieving the data, and potentially secure research funding to compensate the organization for the data retrieval cost. • **Develop a data-gathering plan.** Plan what data need to be obtained to address the research problem. Assign levels of difficulty in obtaining the data and identify must-have versus nice-to-have data to prioritize data retrieval.
Research outcome	
Sharing results. *Managers fear that sharing results compromises the firm's competitive position; they may not understand the long time lag and level of abstraction of academic publications*	• **Be flexible on the level of visible involvement of the practitioner in the outcome.** Managers might find value in co-presenting findings internally or at industry conferences, and in co-authoring industry reports and managerial articles. These activities present the manager as a thought leader and provide visibility in his/her industry. Some organizations might also be interested in building credibility, which is often the case in start-up and new product-launch situations. • **Emphasize that it will take a long time before findings are published.** Research findings may be published only years after the data provision. Depending on conference and journal submission plans, contractual agreements regarding an embargo for release of findings can be used to address managers' concerns. • **Clarify the type of results that will be published.** Research publications will not contain highly context-specific results (e.g., descriptives) and absolute figures can be avoided if desired (e.g., by standardizing variables).

Research problem

  Co-develop research questions. Practitioners and academics differ regarding their views on research problems. Interestingly, most of the research center members we gathered feedback from, such as CTF, CSM, SSF, CSI, or the Cambridge Service Alliance, conduct some type of co-creation workshops and events that bring practitioners and academics with an interest in a general research topic together to jointly develop research questions. This is also consistent with the feedback from Roland Rust at CES: "It is important to recognize that practitioners may be able to identify a general problem area, but probably can't define a publishable research problem." Mary Jo Bitner from the Center for Services Leadership at Arizona State University recommends to "look for the sweet spot where the research addresses important managerial issues for the company but also has the potential for theoretical/generalizable conclusions". Academics thus need to be prepared for the fact that they likely need to co-develop the research question, which of course requires some flexibility and the ability to convince the companies to select a very specific question out of this more general problem area. It is therefore relevant to set the right expectations, in particular regarding the scope of the project, in order to have a clear view of what constitutes a satisfactory outcome from the company's perspective.

  Frame your research in context-specific way. Once scholars are aware of the different expectations with regard to generalizability, they can adapt and frame the research problem accordingly. The following example illustrates this nicely. Schaefers et al. (2016) were interested in contagion of customer misbehavior in the sharing economy. To examine their research question, they collaborated with a car-sharing provider. For the authors, car sharing was "only" the empirical context, since they aimed to generalize their findings to the sharing economy at large. In contrast, the car-sharing provider's main focus was to encourage its members to treat the cars with more care. Adapting the abstraction level of the research

problem in communications with practitioners made it easier to find a common denominator.

Think in terms of 2-in-1 solutions. When implementing research questions, we recommend thinking in terms of *2-in-1 solutions*. The managerial world often expects tailored solutions that might lead academics to compromise on quality by having to amend established instruments and procedures (Anderson et al., 2001). However, we also see the tailored approach as an opportunity to spark practitioners' interest, as is shown in the following example. Wittkowski et al. (2013) were interested in firms' intention to use non-ownership services, such as equipment that is accessed through a service rather than through ownership. For this, the authors wrote letters to various leasing companies explaining their research project, and this sparked one company's interest. To reach common ground with the potential collaboration partner, the researchers offered to add various items to the questionnaire that were purely of interest to the company. For the results presentation, the researchers provided additional minor analyses in order to satisfy the company's requests for more context-specific results. In the researchers' view, this seemed like a fair investment in exchange for the benefits from this collaboration, which provided the funding of the quite costly B2B data collection involving CIOs.

Clarify the scope of the project. To address the different realities and priorities with regard to specificity, we first recommend having an explicit exchange about the expectations of the key objectives of the research, its scope, and the process. To do this is particularly important for companies new to collaborating with academics. We recommend that this includes discussing the differences in the roles of consultants versus academics, since practitioners often view researchers as consultants (Rynes, Bartunek and Daft, 2001). There is one major difference relevant to our context: Consultants are paid to address the objectives of the client company, so tailored solutions and switching the goalposts (including the research problem) during the project are feasible, although potentially subject to additional

billing discussions. By contrast, when researchers collaborate with an organization there will usually be a goal overlap, but it is very unlikely that the aims of the researchers are fully aligned with those of the company. The researcher might subordinate his goals to get access to data, but this will have its limits when the core aim of the academic is compromised. Furthermore, because of the often rather narrow research interest (Alvesson and Sandberg, 2013), switching the research problem during the project is disruptive, likely leading to project termination. In view of this, it is advisable to clarify expectations with regard to the scope and specificity of the research problem at the beginning, and define and fix the goal of the project in writing.

Present the big picture to practitioners. Despite academics usually choosing very specific research questions, we recommend providing a "big picture" story to practitioners, even though the scholar's own research might only be a small piece of this picture. A sound literature review is the basis for an academic article, mainly to identify knowledge gaps and to carve out the theoretical contribution of their work. However, literature reviews have also been identified as one potential instrument to bridge the practitioner–academic gap (Bansal et al., 2012). Even though academics typically only present their own research, we recommend making a "digestible" version of the literature review part of the results presentation in order to accommodate the practitioner's preference for a broad scope of the research problem to support their managerial decision making and learning.

Research resources

Create a network of practitioners and engage with them. Practitioners and academics have different access to research resources. To leverage each parties' resources, we recommend that academics invest in creating a network of practitioners in the field of the author's research area. Almost all members of the research centers, such as Bo Edvardsson and Per Kristensson from CTF, Thorsten Gruber from CSM, and Yongchang Chen from the

ISE, emphasize that research collaborations often develop over time because trust has to be built. Partners typically first engage in smaller activities such as guest lectures, small consultancy, or student projects. Thorsten Gruber from CSM recommends as follows: "Start small and do it well – deliver excellence so that they want more." Similarly, Yongchang Chen notes that consultancy projects are often inroads to more research-related projects because the researcher has proven to be of value and already has insights into the company.

These recommendations are consistent with the managerial literature that identified two common networking mistakes: (1) people put off networking until they need it; and (2) people ask for too much in the early stages of a relationship (Kolowich, 2016). Anecdotal evidence from a staff survey at one of the author's universities suggests that many academics do not have sufficiently substantial industry networks. When the academics were asked how many practitioners they can call and ask for a favor, only a fraction reported a reasonable number. Building up and maintaining a strong network of practitioners is a good investment for leveraging different data realities and priorities.

A corporate network can be developed by attending practitioner events, leveraging contacts from the university, guest lecturers, practitioners who react to the university's and researcher's dissemination activities, and former students. In addition, research organized through research centers can formalize regular network sessions, enabling business leaders and researchers to mingle, share ideas, present research, and discuss business issues. At CSI, PhDs and post-docs are required to spend time at a partners' site as part of their project.

Choose relevant research areas. To gain access to data, we further recommend choosing relevant and interesting research areas. This relevance can be related back more easily to contextualized questions and general management challenges. For example, how do incumbents become more agile, digital, or innovative? Rather than deducing research questions merely from the literature, which potentially leads to "incremental gap-spotting

research" (Alvesson and Sandberg, 2013), we recommend also considering deducing research questions and ideas from real-world issues by skimming through practitioner journals, thought-leadership pieces from leading consulting firms, industry journals, and practitioners' newsletters. It may also be useful to attend conferences, sales events, and webinars to gain an understanding of current trends and developments. We recommend that researchers try to identify what areas and phenomena marketing practitioners are grappling with and consider worth speaking and writing about.

Sell cutting-edge research skills. Another recommendation to ease data access is to signal and prove that scholars have value to add in comparison to internal company researchers and external consultants. Over and above needing project-relevant skills (e.g., knowledge about the topic at hand), access to cutting-edge academic literature and thinking, and having sound method and sophisticated analytical skills, are important and can be key differentiators in comparison to internal company units. As Moe and Ratchford (2018) point out, academics often work comfortably using complex methods that allow them to analyze company data in alternative ways to produce more valid results that should lead to more effective decision making. For example, skills in machine learning, according to Dhar (2013), are "fast becoming necessary for data scientists as companies navigate the data deluge and try to build automated decision systems that hinge on predictive accuracy". Moreover, skills in quantitative text analysis (e.g., Benoit, 2019) can also be considered as highly useful for signaling to practitioners the value of exchanging their unstructured data against insights provided by academics.

A dataset can have many forms and shapes. We identified data recency as another area with differences. Despite managers perceiving recent data as a requirement for valuable insights, companies might be reluctant to share this kind of data with someone outside the organization. In this case, we recommend not treating a "dataset" as a dichotomous variable,

since it can have many forms and shapes when discussing data access. Negotiation tactics suggest that an effective approach is to expose people to a number of options to choose from in order to lead the counterpart away from thinking about a simple yes/no option. Thus, whereas it might be preferable to gain access to a recent, comprehensive "perfect" dataset, for academic research this might not be necessary. We recommend keeping in mind that there are endless variations of most datasets, including omitting certain regions, customers segments, or products, and/or leaving out various variables. Often companies do not want outsiders to have too transparent a view of the company's overall revenue or revenue model. Omitting parts of this data can reduce barriers to sharing. Furthermore, if academics need sensitive data that becomes less sensitive over time, they can ask for older data (e.g., last year's data or older) for the academic portion of the project.

Be aware of legal frameworks. Legal limits and operational barriers to giving access to data have also been identified as an area with different realities and priorities. With increasing consumer privacy concerns (Lwin et al., 2016) and highly publicized scandals about social media companies leaking their users' data (e.g., Cambridge Analytica), companies have become increasingly careful about sharing customer data. With this in mind, when aiming for access to customer data, we recommend that academics familiarize themselves with the legal frameworks and restrictions on data sharing. It would go beyond the scope of this article to review the regulations in various regions of this world, yet, as an example, the EU has recently enforced the new General Data Protection Regulation (GDPR), which specifies that companies "can't further use the personal data for other purposes that aren't compatible with the original purpose of collection," and that if such personal data are to be used, individuals need to give their consent (EU, 2018). In a European setting, it is therefore vital to know what qualifies as personal data in order to have an informed discussion about data provision.

Furthermore, researchers can expect that the managers involved in initial discussions are unlikely to be sufficiently familiar with the details of data protection regulations. These managers will, before coming to an agreement, consult their legal departments to deal with questions on data privacy compliance. Furthermore, Mary Jo Bitner shares the recommendation to be "prepared for serious and sometimes lengthy review by the company's and university's legal departments prior to agreeing to terms of the engagement". Thorsten Gruber from CSM stresses "the importance of sorting out all legal (and ethical!) issues. They can significantly delay or even kill off projects." These issues make it even more important for the academic to know enough about these regulations to frame the data request from a compliance point of view and to signal professionalism and competence to their corporate partners, who will then be more confident in presenting the data request to their legal department.

Relegate to data and privacy regulations at universities. One aspect worth mentioning in conversations with practitioners about data protection and privacy is that – again depending on the local regulatory framework – in most countries, universities have strict data protection principles, and regulations for data collection, analysis, and storage (see, for example, the policy by the University of Surrey, UK: https://www.surrey.ac.uk/information-management/data-protection.) Referring to strict university regulations on data management might be helpful in overcoming barriers to data sharing. Colleges and universities are among the institutions that people generally trust (Ladd, Tucker and Kates, 2018).

Emphasize that only anonymized data are needed. To dispel concerns, it is important to create awareness about the data requirements: that is, that academic research generally does not need individual customers to be identified. For example, when customer data are provided, there is no need to give access to names, exact addresses, and the like. Often, anonymized data is all that is required for theory development and testing. In fact, the

academic would be breaking EU law if s/he analyzed personal data other than that required for the research question at hand. We therefore recommend ensuring no personal data are transferred that would allow an individual to be identified.

Provide sample articles to reduce barriers. In our experience, giving sample articles, ideally from previous collaborative research projects of the authors, is a valuable tool for reducing the barriers and elucidating that the competitive threat and data protection issues from an academic article are generally negligible and can be mitigated effectively.

Research process

Study your audience before interacting. There are different realities and priorities relating to the research process linked to different personalities, communication styles, approaches, and priorities in knowledge generation. It is thus important to study the audience before interacting, not only in the initiation phase but also in the collaboration phase.

Academics must recognize that managers have to be comfortable with any models produced from the research, or they will not use them in their decision making and will become reluctant to collaborate with academics in the future. As managers are generalists, simpler models tend to work best. We thus recommend potentially creating different variations of the research model and focusing on the main effects if needed.

In addition to the above, Robert Ciuchita from CERS states that proving rigor is less necessary when presenting to top management, since they assume that internal research departments have vetted the results and often the university's reputation provides sufficient credibility anyway. Mohammed Zaki from the Cambridge Service Alliance shared that one practitioner he works with has stated that to present his research to the top management he needs to synthesize the entire project on five slides. That is, presentations and reports have to be short and to the point, with details moved to an appendix.

Create different result presentations. We recommend viewing results presentations

and reports for a managerial audience separate from those for the academic audience. This is echoed by Dominik Mahr from SSF, who stated that he found it extremely difficult, if not impossible, to create a results presentation that serves both audiences simultaneously. The reason is, in our view managerial audiences often think in descriptive result categories (for example, "X% of people do Z") and more in problem–solution patterns.

This difference in perspective also relates to the importance of statistical significance in an academic presentation where academics aim to generalize their results. Practitioners who provided data from which results were generated often do not care much about significance. In fact, significance is a given, as managers are only concerned with large enough effect sizes that are of managerial relevance, which would naturally be statistically significant.

Robert Ciuchita from CERS noted that another part of the problem is that managerial audiences are used to consultancy-type presentations with action titles and an explicit verbal interpretation of the key takeaways and the "so whats". In contrast, academics tend to structure their presentations based on literature gaps and contributions, often show complex relations, and are used to presenting results separately from their implications. In view of this, we recommend that researchers adopt a more managerial style when presenting to managerial audiences. That includes mainly providing interpretations of their findings and addressing questions such as, "What do these findings mean for your product, segment, and distribution channel, and the company overall?" and "How can your company act on these findings?"

Try to be "bilingual". With regard to communication with practitioners, we recommend that academics try to become "bilingual" and speak both the academic and the managerial languages. Academics need to be able to engage managers with a compelling story about what the benefits are to the organization. In particular, researchers should focus on the problem they are solving for the manager, not the research problem they are interested in investigating. Previous literature states that "the most recognized source of disconnection

stems from issues of communication, especially inaccessible language widespread in jargon-laden academic writing" (Browne, O'Connell, and Meitzner Yoder, 2018). When communicating with managers, academics should therefore acknowledge and indeed expect different world views and communication styles.

__Use inductive and deductive approaches simultaneously.__ Differences relating to the research approach arise from the fact that academics usually deduce their research assumptions from theory (deductive), whereas practitioners induce them from managerial problems or data (inductive). The latter does not require *a priori* assumptions on the relationship of variables (Dhar, 2013), which can be very useful but can also be a signal for a non-rigorous, arbitrary, and results-fishing approach. However, we feel that it is useful to identify interesting and managerially relevant research questions and results that might not have emerged from the theory. With this in mind, aiming to follow both approaches simultaneously is advisable. Specifically, when discussing a collaboration with managers, scholars should have solid knowledge of the existing research and potential theoretical approaches (deductive), and within this frame allow themselves to be inspired by managerial phenomena (inductive). In this way, having some flexibility on the research question will help to initiate and succeed with the collaboration.

A solid knowledge of the literature also allows scholars to provide answers to open managerial questions from the existing literature and at the same time steer the discussion towards unsolved areas that are of interest to academia. We view this approach as different from what McAbee et al. (2017) condemned as the "HARK approach" (Hypothesize After Results are Known) since our recommended approach does not mean that theory is fitted *ex post* to results, but that it is fitted *ex ante* to the situation. This is exactly what Moe and Ratchford (2018) argue, that we as scholars have a competitive advantage in knowledge generation because frameworks and theories guide us in identifying which connections

warrant meaningful investigation.

What academia can do to align data realities and priorities is to challenge standard practices. This is nothing that an individual will be able to change, and it is not going to change overnight either, but if scholars want to leverage the opportunity of the growing "data ocean" and avoid forced HARK-type research, they will need to develop better standards for rigorous inductive research. In our traditional minds, qualitative, unstructured text data (for example, from focus groups and Facebook posts) allows for theory development (e.g., Hennink, Hutter, and Bailey, 2011). However, in agreement with Hambrick (2007), we view data-driven, atheoretical and pre-theoretical work as instrumental for academic progress, since it can build the basis for others generating new theory. This approach can also build the bridge between the academic and managerial worlds, since interesting real-world phenomena can be picked up. For now, we recommend referring to the literature that calls for more flexibility and choosing journals for submission that are more willing to consider novel approaches – such as the *Journal of Service Management* and the *Journal of Service Research* – to deal with this current misalignment. Over time, the community will develop standards governing what is acceptable and what is not.

Prioritize relevance and rigor depending on the research stage. The literature portrays practitioners as being more focused on relevance, and academics as being more focused on rigor (Aram and Salipante, 2003; Bansal et al., 2012). We do not want to repeat the argument about whether these two criteria are mutually exclusive or can be achieved simultaneously (Baldridge et al., 2004), since we recommend treating the criteria differently depending on the stage of the research project. Research projects typically have the following stages: (1) reviewing the existing literature on a topic area; (2) identifying a research question; (3) choosing a theoretical foundation; (4) collecting and analyzing data; and (5) writing up and presenting the results. In these five stages, there is one in which relevance should be top

priority, and that is the choice of an interesting, and thus relevant, question. In order to carry out top-quality research, rigor should be a priority in all the other stages. With this in mind, when collaborating with practitioners, scholars should clarify in which areas of the research process managerial influence will be valuable. Allowing practitioners to influence *what* the research will investigate is likely to enhance its relevance. At the same time, allowing them to influence *how* the research is conducted will likely compromise rigor. Following this approach, academics should not feel that a push for more managerial relevance compromises rigorous, high-quality research (Bartunek and Rynes, 2014), but it might push us to work on more relevant questions.

Identify a project owner. Once a collaboration agreement has been reached, Mary Jo Bitner advises that research projects should "identify a project owner (often a high-level executive) and an onsite/day-to-day partner within the company to assure the project moves along". For longer-term relationships and in research center structures, it might be advisable to identify a "key account": that is, a team member who is dedicated to nurturing the relationship with a special partner of the center. We further recommend setting manageable and clear milestones for the outcomes and the length of the different stages that are consistent with managers' time horizons and will keep them engaged. Setting smaller milestones and managing expectations that can be met, or perhaps even exceeded, will enable academics to conduct mutually satisfactory collaborative research.

No urgent questions. Different timing expectations (i.e., anecdotally speaking, practitioners think in days and weeks, and academics think in months and years) can be a substantial barrier to aligning data realities and priorities. From personal experience, we have learned that working on urgent questions, meaning that results are needed to make urgent managerial decisions, is not recommended. This might sound like a contradiction of the recommendation to work on managerially relevant questions, but if we think of urgency and

relevance as being two different dimensions, we recommend not engaging in research questions that are both relevant *and* urgent. With the different timing expectations in mind, this will likely lead to disappointment, and thus, if a scholar senses that the practitioner is seeking to find answers to their urgent questions through this research, we recommend staying away from this collaboration unless you can quickly produce results for managers and the scholar is highly experienced in the area of interest.

More strategic issues and upcoming topics are more prone to result in fruitful cooperation. Sentences like "We always wanted to know this," or "At some point we need to get our heads around …," serve as markers for such types of projects. This is in line with Mohammed Zaki's feedback that practitioners sometimes expect academics to be forward-thinking and to identify and undertake research on upcoming problems. Examples of such topics include questions on IoT, platforms, robotics, AI and Blockchains (cf. Wirtz, 2018; 2019). Many companies find it very relevant to investigate the impact of these technological developments on their industry or their organization, but they are often not yet high enough on the urgency scale to lead to resource-intensive commitments. It will be easier for practitioners to accept academic timescales for such non-urgent types of questions.

Present preliminary results shortly after data collection. Another remedy to overcome different expectations with regard to the timescale of a research project is to consider the different audiences when preparing the results presentation. We recommend producing a preliminary results presentation or report soon after the data collection has been finalized to satisfy the desire from the managerial side to see results quickly. This presentation or report does not need to include the final research model and can be updated at a later stage after the analysis has been completed. Often, simple frequencies, cross-tabulations, and correlations are all that are needed for such an initial report.

Make data provision easy. Even if a practitioner is willing, it can be costly to retrieve,

align and transfer structured, semi-structured, and unstructured data. As a result, companies might be reluctant to invest in this effort. Depending on the situation and the value of the data, academics might want to offer their own time to support companies in doing so. Alternatively, and ideally, the projected outcomes of the research are so interesting that the company believes that investing the resources to retrieve the data is worthwhile. Joint funding applications might be another way of generating additional resources to compensate the company for the cost of retrieving the data. In short, academics need to find ways to make it easier for managers to provide them with the data they like to work with.

Develop a data-gathering plan. We further recommend the development of a data-gathering plan. Researchers and managers need to plan together what data are available to answer the research question, and assign levels of difficulty in obtaining that data in the format needed for the investigation. This information can be used to align the research objectives with the ability to obtain the necessary data. Dominik Mahr from the SSF recommends explicitly identifying "must-have" versus "nice-to-have" data early in the process, and making clear that getting access to the must-have data is a condition of the collaboration.

Research outcome

Be flexible with regard to the visible involvement of practitioners in the outcome. In addition to the above, we further recommend flexibility with regard to the visible involvement of practitioners in the outcome, which means academics might want to offer options from co-presenting findings internally in the manager's organization and at industry conferences, and potentially co-authoring industry reports and managerial papers. These activities present the manager as a thought leader, provide him/her with visibility in the industry, and help to generate publicity for the research overall. Co-authorship on academic articles may also be an option but is likely to be of interest only to a small fraction of

practitioners. However, some more research-oriented firms might find it of value to position their firms in the academic community. Furthermore, smaller firms such as startups and firms that launch innovative breakthrough products may view being associated with academics from reputable universities as an opportunity to build their credibility.

Emphasize that it will take a long time before findings are published. Offering the option of data-source confidentiality in the paper relates to practitioners' fear that research results will – when published – compromise their competitive position. In our view, this barrier is frequent and substantial, but looking at it in reality it is nowhere near as threatening as it seems. Firstly, not disclosing the company that has provided access to the data will make it less likely that competitors can decipher concrete competitive insights. Secondly, we recommend pointing out the common publication timeframes. Yongchang Chen from the ISE experienced that explaining that, due to the peer-review process, the results will only be publicly available years after the data provision was sufficient to reduce management's anxiety to the extent that they agreed to collaborate. However, if managers are still worried, an additional option scholars can consider is contractually agreeing to a certain grace period for the publication date, meaning that results will only become publicly available when agreed, which can be one or two years after data access has been granted. This is often the timeframe academics typically need anyway to get to their first conference presentation or journal submission.

Clarify the type of results that will be published. Another possible solution to dispel managers' fears that results might impact their competitive position is to clarify *the type of results* that will be published. Practitioners might be unaware that very context-specific results are unlikely to be part of an academic publication. The fact that academic research questions are more abstract and less context-specific than managerial questions actually becomes an advantage in reducing managers' concerns. If descriptives are needed (e.g.,

showing means or standard deviations), then absolute figures can be avoided by reporting standardized variables only, applying some multiplier, or showing percentages.

CONCLUSION AND LIMITATIONS

Organizations are often drowning in data, leading them to use only a fraction of their data to generate insights and support decision making (DalleMule and Davenport, 2017). At the same time, researchers spend increasing amounts of time, effort, and financial resources to collect data that yield relevant academic results. In this article, based on the above description, we portrayed companies as *data gatherers* and academics as *data hunters*. Despite a substantial body of research on the practitioner–academic gap (e.g., Amabile et al., 2001; Anderson et al., 2001; Markides, 2007; Birkinshaw et al., 2016; Hambrick, 2007), no research has taken a closer look at this gap in relation to data realities and priorities. Our article fills this gap and identifies four dimensions of data realities and priorities relating to the research problem, resources, process, and outcomes (Table 1). Based on this framework, it identifies recommendations on how to leverage these data realities and priorities for the benefit of academics and practitioners alike (Table 2).

Despite having integrated the feedback of the leading service research centers around the world, our research and the approach taken come with the limitation that these views, experiences, and approaches are personal and subjective, and hence subject to debate. However, the authors of this article have either worked as practitioners or successfully collaborated with the managerial world in their academic research, and as such have regularly managed to leverage data realities and priorities for the benefit of all partners involved. We hope that our recommendations will help more academics harness the tremendous opportunities that gaining access to corporate data can have for advancing research and theory development.

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