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What Is Different About Digital Strategy? From Quantitative to Qualitative Change

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Abstract. The recent attention paid to the challenge of digital transformation signals an inflection point in the impact of digital technology on the competitive landscape. We suggest that this transition can be understood as a shift from the quantitative advances that have historically characterized digital progress (e.g., Moore's law, Metcalf's law) to qualitative changes embodied in three core processes underlying modern digital transformation: representation, connectivity, and aggregation. We consider the implications for firm strategy and raise questions for future strategy research.

Keywords: digital transformation • digital technology • representation • connectivity • aggregation • firm strategy • digital strategy

1. Introduction

Digitization has accelerated in the postwar era. However, even as the exponential growth rate of processing capacity relative to cost predicted by Moore's law has assumed an almost taken-for-granted status since its first articulation in 1965 (Moore 1965), something dramatic has changed in recent years. We suggest that this "something" can be understood as a transition from quantitative improvements to qualitative changes. While we do not minimize the miracles that have led to, and been enabled by, the exponential improvement in processing power, storage capacity, bandwidth, and their associated costs, we suggest that their impact has been well accommodated within the existing strategy canon until recently. Therefore, we focus on the qualitative changes that interact to produce truly novel outcomes. We posit that the changes we highlight demand a re-examination and expansion of the strategy principles that have guided the field's approach to technological transitions thus far. This is a conversation we hope others will swiftly join—to challenge, complement, and ultimately improve our collective understanding of firm strategy in the digital era.

Consider the example of recorded digital music: The first major digital transition was from analog to digital formats (from LPs and cassette tapes to CDs). This was mainly a shift in *representation*, from the capture of physical markers (grooves in a record; magnetic distributions on a tape) to digital markers (ones and zeros on a CD), with implications for fidelity and replicability of the information and technical capabilities of industry participants. The second transition was from physical format to downloadable formats—the shift from CDs to MP3 files distributed not through physical means but through platforms like Napster and iTunes. This was essentially a shift in *connectivity*, which enabled music content to be accessed through a digital network, with implications for access (any song posted on the network was now available to all network members), governance (redefining the rules of behavior and legality), and form (the unbundling of albums into individual songs). The third and current transition, exemplified by services like Spotify, entails a shift from requested content to suggested content. More than a change from downloads to streaming, this is a shift primarily in *aggregation*. By combining and analyzing the past content requests of numerous other users as well as rating and other usage data regarding the focal user, it is now possible to proactively customize suggestions for a specific user and even to predict the likelihood that the user will follow the suggestion. This shift from responsive to predictive streaming changes the relationship between producers and consumers and impacts the very nature of consumer demand, choice, and preference.

The first transition from tapes to CDs could be well characterized by utilizing tools of traditional competitive and technology strategy (e.g., Abernathy and Utterback 1978; Porter 1980, 1985; Tushman and Anderson 1986; Prahalad and Hamel 1990). Understanding the second transition required the addition of new concepts, particularly surrounding economies of scale and network effects in network environments (e.g., Katz and Shapiro 1994, Shapiro and Varian 1999, Rangan and Adner 2001). This enriched the strategy lexicon and opened up new subfields for study. We suggest that understanding the current transition—to hypercustomized, predictive, self-improving technologies—similarly requires the addition of a new conceptual apparatus, which will broaden the scope of inquiry that researchers can pursue and educators can deploy.

Our article focuses on the qualitative shifts and interactions embodied in the three core processes underlying digital transformation: representation, connectivity, and aggregation. We suggest that the interactions among these processes have important implications for a number of central strategy concerns, including the resource-based view (Wernerfelt 1984, Barney 1986)—the analysis of data and algorithms as resources; the behavioral theory of the firm (March and Simon 1958, Cyert and March 1963) in terms of the impact of algorithmic decision making on bounded rationality and organizational learning; transaction cost economics (Coase 1937; Williamson 1975, 1985) in terms of the decline in search and contracting costs; diversification (Chandler 1962, Rumelt 1982)—for example, understanding the nature of relatedness and the choice of corporate scope based on data; organizational design (Simon 1947), such as organizing without hierarchy and designing human–algorithm collaboration; and technology evolution (Abernathy and Utterback 1978)—for example, the impact of artificial intelligence (AI) and autogenic data on how organizations work and, ultimately, the possibility of new business models and the very nature of competitive advantage (Agrawal et al. 2018).

2. Digital Foundations

Digitization does not require us to abandon the basic conceptualizations of the economic phenomena we are familiar with. Transaction costs (Coase 1937) and bounded rationality (Simon 1957) as conceptual building blocks and resource (Barney 1986) and industry analysis (Porter 1980) as analytical tools remain important guideposts on the journey. At the same time, it is critical to recognize the need for new additional tools and conceptualizations (see also Levin 2011, Goldfarb and Tucker 2019). In this spirit, we identify three foundational processes that, in our view, explain much of the variety of phenomena that are subsumed under the rubric of "digital transformation." We propose that any example of contemporary strategic interest—whether it be Alibaba's e-commerce platforms, Instagram's apparently unlimited appeal to teenagers, Tesla's efforts in autonomous driving, or the startling popularity of multiplayer online gaming as a spectator sport—can be usefully deconstructed into these core components.

2.1. Representation

Digital transformation begins with digitization. It is the digital representation of information that enables analysis and algorithmic manipulation. It has become a truism to state that data are the new oil, the key input to the engine of the information age. However, the explosion in the quantity of data available has been accompanied by qualitative revolution in the representation of these data that underlie digital transformation.

In order to appreciate the scope of what digital representation has evolved into, consider its roots. Early digital logic was famously used by militaries to compute ballistic trajectories more rapidly than human calculators. This is an example of converting information from one logical form (analog tables and written equations) to another (data and programs) to generate digital data and insight. Further, the transition from LPs to CDs is an example of converting analog information into digital form. The early phases of the digital revolution were characterized by such conversions, as paper ledgers transitioned to digital spreadsheets. A qualitative shift occurred when aspects of reality that were *not* considered data in the past—the location of people and cars; the on/off status of a living room light switch—were captured, digitized, and incorporated as inputs into algorithmic processes that produce predictions regarding traffic patterns or electricity consumption.

The growing ubiquity of sensor technology has created new variants of digital fodder and expanded the "on ramp" onto the digital transformation process; simultaneously, there has also been rapid development of the "off ramp" that involves the transformation from the digital back to the physical world. This is a mirror process—also characterized by quantitative acceleration—in which digital signals are transformed into analog actions. Automation, robotics, and 3D printing are the most visible manifestations of this process, which is foundational to the idea of the "fourth industrial revolution." The resulting deluge of data would be more of a hindrance than help if we only dealt with it using human-bounded rationality; however, it is now possible to represent large volumes of data and the actionable insights they contain in the forms of algorithms. Machine learning is essentially a form of function approximation (Abu-Mostafa et al. 2012, Varian 2014). Critically, there is limited need for human guidance in functional form selection, and the resulting function is not always easy to interpret for humans (Mullainathan and Spiess 2017). This ability to represent data algorithmically rather than in a human-guided form (as in traditional descriptive statistics or statistical modeling for hypothesis testing) is qualitatively distinct in terms of what it implies, both for human-bounded rationality and in terms of raising the intriguing question of how to approach the potential for competence without comprehension.

2.2. Connectivity

Digitization creates new connections and enhances existing connections among objects, individuals, and organizations (e.g., Siggelkow and Terwiesch 2019). From the one-to-one connectivity of email or text messaging to the many-to-many connectivity of social media, e-commerce platforms and sensor-embedded production lines today instantiate the enormous increase in potential connections among economic actors and inputs into economic decision making. The sheer size and density of the network of connections as well as the range and number of new actors who are part of the network of connectivity are the first major effects of digitization. Greater network density has generally followed Metcalfe's law in yielding exponentially greater network value (e.g., Metcalfe 2013). The quantitative explosion of connected points has enabled the emergence of completely new business and organizational models, some of which have cannibalized their nondigital equivalents.

However, the shift from connectivity-on-demand to connectivity-by-default has resulted in a qualitative change that goes beyond quantitative increases in network density. As products and services become more digitized, every product or service can be used to facilitate connections. This transition to always-on connectedness enables revolutions in search, monitoring, and control. For example, whereas the success of a search used to be assessed in terms of accuracy and comprehensiveness of results (whether in the search engine battles between Google and Yahoo or the knowledge management system quest for information retrieval), search success is now assessed in terms of context-specific relevance—"is it right" versus "is it right for me, right here, right now." Whether from the perspective of a consumer engaged in information search or a producer engaged in information targeting, the challenge has shifted from broadening the search space to assure more comprehensiveness to an ever greater urgency to winnow down information and choices into manageable sets.

Indeed, as the digital revolution has shattered the constraints of information search and availability, it has heightened the constraints of deliberation and choice (Rangan 2000). Questions of "what do I erase" and "what do I ignore" have become critical. It is perhaps not coincidental that the phrase "TMI," or "too much information," made its first appearance in the *Oxford English Dictionary* in 2009. Thus, how firms allocate their attention has become a more important strategic decision than ever (e.g., Ocasio 1997, Piezunka and Dahlander 2019).

2.3. Aggregation

Finally, beyond the quantitative growth in data storage capacity and reduction in storage costs is a third qualitative shift—that of data aggregation. A qualitative shift arises from the ability to combine previously disjoint data (e.g., location, search query, and social network) to answer questions that were formerly impossible to address.

For example, combining multiple types of data on individuals changes what we can say about their health risks or their financial soundness. Combining data related to human resources with traditional supply chain data provides managers an unprecedented opportunity to understand their internal organization and its constituents. Enhancing such synergies explains the drive toward diversification and the blurring of boundaries at firms such as Oracle and SAP. While that is an energizing vision for many, it has a few dystopian shades as well. Governments can now have more information regarding their citizens than they ever could in the past, raising a specter of Orwellian observation and control. Similar concerns could apply to the relationship between corporations and their employees. The new corollary to *Star Trek*'s Borg mantra of "you will be assimilated" may be "your data will be aggregated."

2.4. Interactions

While each of these effects of digitization is significant, truly dramatic changes become visible when they interact and reinforce each other. For example, connectivity and aggregation, in conjunction, underlie a host of new business models such as TripAdvisor, Napster, Groupon, Yelp, and the iTunes store. In each of these instances, a combination of enhanced connectivity and data aggregation has produced new functionality and opportunities for value creation and capture. Advances in connectivity and representation produced intelligent social media platforms such as Facebook, WeChat, and LinkedIn, where recommendations are made for potentially useful connections among individuals who may not even be aware of each other's existence. Within organizations, messaging platforms such as Yammer and Slack attempt to bring the same benefits. Combinations of representation and aggregation form the backbone of the dramatic increase in consumer analytics (including credit scoring) as well as the burgeoning field of organizational analytics. When connectivity, aggregation, and representation all come together, we see developments such as self-driving cars, the Internet of things, Spotify, and the Chinese state's social credit system.

To provide a concrete example, "digital twins" currently enable physical processes (e.g., the wear and tear of a jet engine) to be represented digitally in the form of a simulation model. Such a model derives its predictive power from the dynamic connectivity to the actual engine being modeled, aggregation of data across similar engines in other planes, and the use of algorithms to extract predictive insights from these data. Crucially, the resulting model enables not just preventive maintenance but may also enable virtual experimentation for design improvements. As McAfee (2019) argues, simulation supports a dramatic increase in the effectiveness of search for efficiencies, given that virtual prototyping does not face the same resource constraints as prototyping in the real world. Connectivity, aggregation, and representation lay the digital foundations on which such virtual prototyping can take place.

There may also be strong complementarities between these processes, as the development in one increases the value of the other. Aggregation enables potentially better connectivity (e.g., in the form of "friend" suggestions or supplier selection), just as more connectivity produces data that can benefit from being aggregated (e.g., data from multiple users of a particular firm's services can improve the rating of the firm's creditworthiness). In order to truly utilize this volume and breadth of data usefully, algorithmic representation becomes even more valuable, as human cognition runs into serious challenges at this scale. With data aggregated in a general access, cloud-based pool, both the mass of data as well as the insights from algorithmic representation can be shared equally and instantaneously among members through "always on" connectivity. Once an improved insight is generated, it can be deployed across all nodes of the network, yielding an across-the-board increase in system efficiencies.

Put simply, *as connectivity and aggregation erode transaction costs (and in turn accelerate as transaction costs erode), the resulting increase in transactions enhances the potential for new and more kinds of data; consequently, advances in data representation become ever more valuable in the effort to process these data and mitigate the constraints of human-bounded rationality*. In turn, this spurs further investments in connectivity and aggregation, driving a positive feedback loop. The increasing velocity of these mutually reinforcing changes, driven by the underlying complementarities between these processes, may account for the distinct sense that digitization is creating a dramatic set of recent changes.

3. Implications

What do these core transformative processes underlying digitization mean for firm strategy and strategy research? We highlight a few major areas below, unabashedly raising more questions than we can provide answers to at this point.

3.1. Resource-Based View (RBV): Data and Algorithms as Self-Generating Resources

Fundamental to the question of what digital transformation means for strategy is an understanding of the characteristics of data as a strategic resource (Barney 1986). Levinthal and Wu (2010) introduced a useful distinction between resources that are scale-free (nonsubtractable or nonrivalrous; e.g., brand) versus those that are not (i.e., subtractable or rivalrous resources; e.g., cash). Data are unquestionably the ultimate scale-free resources, but when do they become a basis for competitive and corporate advantage?

In order to understand the complexities that arise from how data are generated and consumed, consider a particularly interesting new form of digital data creation that can be described as "autogenic." This arises when the very act of engaging with data creates new data—for example, the act of requesting a search and reading its results itself creates new data about the requester, his or her interests and habits, and so forth. A specific example is "keystroke dynamics," which is a biometric identification methodology for recognizing individuals based on the manner and rhythm with which they type on a keyboard. Keyboarding rhythm is an example of data that are incidentally generated through the act of engaging with other data. Thus, it is autogenic (self-creating) data in the same manner as the listening preferences created by individual requests for individual songs—generated incidentally to the focal task and usable regardless of original intent. While it may be incidental, it may also be highly valuable—for example, tracking changes in keyboarding patterns may hold a key to proactive diagnosis of Alzheimer's disease. In this case, the criteria of value, rarity, and substitutability must be approached anew—the value of the data resource is determined (and limited) by the deployer's creativity in use. The rarity of the data resource is in the micro (the record of your specific, individual keyboarding data over time) but not necessarily in the macro (the data pool needed to train the algorithms to deliver insight); moreover, the substitutability of the data resource, whether with voice patterns or facial recognition data, again depends on use.

The fungibility of a resource is defined in terms of low decline in value when a resource is applied in its second-best use relative to its first-best use (Montgomery and Wernerfelt 1988, Anand and Singh 1997). A smaller decline indicates higher fungibility. For example, a manufacturing line that is producing value of $100 million in business A may produce either (1) $100 million or (2) $50 million of value when applied to business B. Case 1 indicates high fungibility, while case 2 indicates low fungibility. Data are always scale-free,[1] although their fungibility may vary. Data instantiate the point that fungibility depends not just on the target-use case but also on the other data sources alongside it in the aggregation pool.

If data and algorithms are resources, their replication may be a qualitatively distinct phenomenon from knowledge transfer among humans (Szulanski 1996). On the one hand, issues of stickiness and causal ambiguity might appear less relevant in replicating digital content. Indeed, one might be concerned that costless large-scale replication may imply a homogeneity of beliefs throughout a system that may curtail organizational exploration (March 1991). On the other hand, stickiness may be even more important in the use by humans of the insights generated algorithmically from data. The confidence that human decision makers place in algorithmically derived insight may depend, at least in some cases, on their ability to comprehend the causal structure of the process that generates the insight, and numerous state-of-the art techniques in machine learning do not offer such causal understanding.

3.2. Data, Ownership, and Factor Markets

Simultaneously, it is also rather unclear who should own these data. Does the keyboard user even know that such data are being collected? Is their consent required? If so, should this consent be required for ongoing collection or each successive reuse? Consider another instance: the use of cars as essentially another data-generating and data-consuming device, rather than a vehicle per se. Does the car owner own the data generated by her vehicle or can the manufacturer lay claim to it to (a) use the data, (b) resell the data, and (c) preclude the car owner from selling the data? This is not hypothetical—in an effort to preclude their customers from accessing and modifying data created within their products, General Motors and John Deere, among other manufacturers, argued that ownership of a vehicle does not include ownership of the underlying computer software in a vehicle (Wiens 2015). Alibaba temporarily barred Chinese courier SF Express from taking deliveries from its e-commerce vendors in a dispute over the ownership of customer data (Cui et al. 2019). Thus, issues of interorganizational trust as well as the trust of customers in organizations are likely to become salient in such situations.

With enhanced connectivity, it is also no longer easy to curtail information flow at the legal boundaries of the firm, thereby creating new opportunities and challenges. The challenges surrounding protection of intellectual property (IP) and sensitive information that feeds competitive advantage are obvious. Creating differential pathways for information of different kinds—where to block its flow and where to enable it—is likely to become a more important managerial challenge than has traditionally been the case (Argote 2012).

These issues of ownership and reuse were less apparent in the world of traditional resources (e.g., Barney 1986) but are highly salient in a digital world. How are our current theories of property rights and vertical integration affected when the make versus buy decision at the heart of transaction cost economics (TCE) relates to the generation of insight from the emergence of inadvertent data, and when usage creates the very property that is being transacted? In contrast to Arrow's information paradox, which explored the buyer–seller challenge that emerges from the fact that once information is shared it cannot be unshared (Arrow 1962), data—particularly their algorithmic use—create ownership difficulties; this is because near costless and perfect replication imply that, unlike a physical good, data can be reused, repackaged, and resold ad infinitum. As the combination of autogenesis, scalability, and fungibility becomes more common, we can expect greater variety in observed solutions to the contracting challenges their potential creates.

3.3. Digitization, Replication, and Super-Scalable Business Models

Once a process or some information is in digital format, replication becomes error free and often costless. Consequently, scalability can improve significantly when this property interacts with connectivity. For example, when Amazon develops a better algorithm to match consumers with products, a digital copy of that algorithm can instantly be made available in millions of virtual storefronts for Amazon customers worldwide (e.g., Brynjolfsson et al. 2008). When one self-driving car learns something from its interaction with its local context, the resulting insight can be freely distributed to all cars connected to it through the cloud. This is fundamentally different in terms of speed, fidelity, and impact from process replication in traditional offline businesses.

Aggregation can also enhance connectivity to improve firm scalability. Take the audio speaker market as an example. The technology underlying physical speakers is rather advanced. The barrier to entry is low, as any engineer can easily put together a speaker from off-the-shelf components. Consequently, the market is highly fragmented. With digital technologies, modern speakers such as Amazon Echo or Google Home are connected to various content and services delivered through the Internet, powered by artificial intelligence (AI) algorithms (Alexa and Assistant, respectively) that can interpret users' voice commands and interact with them. As they accumulate more data from each user, they become more intelligent and, hence, attract more usage and more users, enjoy higher scalability, and gain larger market shares. The positive feedback loop creates a supply-side "data network effect" that offers the potential for high barriers to entry (e.g., Zhu and Iansiti 2019). In the smart speaker market, Amazon has opted to license its Alexa platform to other speaker manufacturers, a move that simultaneously enhanced its advantage in data by expanding usage and inputs while allowing for easier entry downstream. Thus, firms positioning at the locus of data aggregation create a powerful position within the ecosystem from which they can simultaneously invite new partners to join and, as shown below, use as a foundation for expanding into new ecosystems (Adner 2013, 2017). New businesses that capitalize on the opportunities in connectivity, aggregation, and representation create the potential for meaningful industry transformation. An analysis of business model innovations in the digital space that decomposes their components along these dimensions may yield fresh insights into the nature of business models and their genesis and diffusion.

3.4. The Digital Transformation of Firm Scope

The potential fungibility of the digital assets that firms accumulate—for example, software capability, data analytics capability, and installed user base—can create opportunities in multiple markets. As these capabilities are increasingly being leveraged to enter new markets, industry boundaries are becoming more blurred. For example, Amazon began as an e-commerce firm. Over time, Amazon became very good at running infrastructure services and reliable data centers to support its e-commerce business. Thus, it was a natural extension for it to offer this service to other businesses through Amazon Web Services, thereby monetizing this capability. Amazon also entered other sectors—including video on demand, virtual assistants, and movie studios—by leveraging its existing digital capabilities, its installed base, and its extensive database of consumer preferences. Similarly, Ant Financial—the financial arm of Alibaba—has leveraged data and analytics to expand its offering from a payment tool (Alipay) to a wide range of financial services that include credit profiling, money market funds, online banking, and health insurance.

Many digital firms also expand their businesses into the territories of their value-creation partners as they grow (e.g., Wen and Zhu 2019, Zhu 2019). Apple chose to offer some of the most popular apps or features by itself on its iPhone and became a competitor to app developers. Many third-party sellers on Amazon competed with Amazon because Amazon sourced the same products from manufacturers and sold them directly itself. FedEx decided to end its express and ground shipping services for Amazon, as Amazon continued to build out its own delivery infrastructure.

The potential for synergies appears much greater in digital-enabled contexts than in the all-physical world in which theories of diversification were first established (Rumelt 1982, Puranam and Vanneste 2016). Extreme fungibility suggests that traditional notions of relatedness may benefit from re-examination. Further, the blurring of industry boundaries implies that firms are increasingly likely to face competition from players outside their industries (e.g., Seamans and Zhu 2014, 2017) and that the nature of their competitive response can shift dramatically in a world of digital asymmetries (e.g., Adner et al. 2019). How companies leverage their digital assets to increase their scale and scope and how they respond to competitors from different industries are important questions for both academic research and real-world practices. Corporate strategy researchers must relish the opportunities to develop and test theories of diversification that can stretch traditional notions of relatedness because of the extreme fungibility of data that arises from the potential for aggregation and algorithmic representation.

3.5. Digital Transformation and the Internal Organization of Firms

How organizations adapt to the forces of digital transformation is itself a topic of interest (Furr and Shipilov 2019). However, within organizations, digital transformation has also created numerous new opportunities for "algorithmic management," in which algorithms and data augment or perhaps even automate managerial work. The way that algorithms and humans can work together is rapidly emerging as a high-interest research area in many fields, such as computer science, human–computer interactions, and consumer behavior, and the implications for organization design are definitely of interest to strategy researchers (Puranam 2018).

Hierarchical control—both the bulwark and bugbear of large-scale organizations (Lee and Edmondson 2017)—may be improvable through digital transformation. The connectivity revolution has implied that managers lose their monopoly on information. A traditional challenge for organizations has been the emergent isomorphism between lines of authority and lines of information flow, thereby leading to the creation of silos, bottlenecks, and breakdowns. For example, consider the excerpt below from a widely circulated recent email from Elon Musk to his employees at Tesla (Bariso 2017):

> Subject: Communication Within Tesla
> There are two schools of thought about how information should flow within companies. By far the most common way is chain of command, which means that you always flow communication through your manager. The problem with this approach is that, while it serves to enhance the power of the manager, it fails to serve the company.
>
> Instead of a problem getting solved quickly, where a person in one dept talks to a person in another dept and makes the right thing happen, people are forced to talk to their manager who talks to their manager who talks to the manager in the other dept who talks to someone on his team. Then the info has to flow back the other way again. This is incredibly dumb. Any manager who allows this to happen, let alone encourages it, will soon find themselves working at another company. No kidding.

The problem highlighted by Musk could be resolved with better connectivity. For managers, this also implies that the legitimacy of their authority cannot come from privileged access to information but must increasingly come from superior abilities to lead and manage; it may also imply greater challenges from information overload.

Extreme connectivity has also spawned outright alternatives to hierarchical organizing. For example, online communities have emerged as a powerful new organizational form for innovation, product development, and knowledge management (e.g., Lerner and Tirole 2002, Lakhani and von Hippel 2003, Zhang and Zhu 2011). In these communities, remotely located individuals are able to collaborate using digital technology that enables coordination through global visibility of coding work in progress as well as tools for managing dependencies and communication among contributors. Scholars have shown that in certain domains of the software industry, this form of organizing—an unambiguous offspring of the connectivity enabled by digitization—enables the aggregation of efforts from numerous contributors and provides credible alternatives to what for-profit firms do (e.g., Greenstein and Zhu 2018, Klapper and Reitzig 2018). The possibility of purely algorithmic solutions to the universal problems of organizing—for example, division of labor and integration of effort—appears to be at the verge of realization in these systems (Puranam et al. 2014).

3.6. Organizational Sensemaking in an Algorithmic World

Algorithmic extraction of actionable predictions has become a powerful new form of data representation. Machine learning is a major departure from the statistical approaches that have historically been the basis of data-intensive insight derivation. From simple mean comparisons and standard deviations to more complicated dashboards and hypothesis tests, previous statistical engines were built on the back of human insight—even if a clerk was being given direction by a dashboard whose logic they did not understand, there was someone somewhere who had laid out an underlying logic for the decision-making rules and processes.

In this regard, cutting-edge techniques such as machine learning produce an additional qualitative shift in how data are used—from representing data to improving human perception of phenomena to prediction, which may or may not involve or be subject to human comprehension. There is a delicate balance that managers may have to strike in this area: they may need to let go of the need to understand in order to satisfy the need to predict. Yet, the risks of ethically repellant outcomes and regulatory constraints and the desire to satisfy sheer human curiosity make this balancing act far from trivial. Theorists may well soon face similar challenges (Puranam 2019). In the meantime, as algorithmic representation becomes ever more effective while becoming ever less comprehensible, the rise of new organizational roles—like Data Storyteller—may not be as surprising as it initially appears. As Weick suggested, a comprehensible and motivating story may have value independent of its veracity (Weick 1995). In a "mixed economy" of algorithmic decision analysis but ultimately human decision responsibility, compelling and clear narratives may become more, not less, important.

These developments have also thrown up a range of complex philosophical and ethical issues, apart from the issue of data ownership that we have already discussed (e.g., should employers be able to read their employee's emails and observe their keystrokes?). For example, algorithms are now increasingly being employed to build predictive models for hiring, retention, and promotion within organizations, and an active area of inquiry in both research and practice is concerned with possible ethical and legal implications of such applications (Cowgill 2019). The risks of institutionalized discrimination, coercion, and control undoubtedly lurk behind the utopian dream of (finally) being able to engineer organizations with the same precision we bring to other complex, human-made systems. The dispassionate examination of these issues by researchers will definitely be valuable.

4. Conclusion

While the basic conceptual tools of our trade—transaction costs, bounded rationality, and the analysis of capabilities, industries, and strategic interaction—remain invaluable, a new set of frameworks may be useful to understand the impact of digital transformation. A focus on the individual components of digital technologies (e.g., data, hardware, algorithms, and networks) might fixate us on the quantitative changes within each component and mask the qualitative changes that arise at the levels of these processes that involve multiple components (as well as interactions among the processes themselves). We have argued that as digital transformation continues, the impact of three processes that have witnessed qualitative changes—representation, connectivity, and aggregation—and their interactions will be more pronounced. These processes will continue to push firms in all industries to create and capture value differently, develop new business models and ecosystems, manage new forms of intellectual property, grow scale and scope differently, and create new opportunities and challenges for organization design and management practices. Digital transformation undoubtedly offers exciting times ahead for strategy researchers.

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Endnote
[1] The scalability of a resource is distinct from its fungibility. Whereas fungibility refers to the relative gap in value between the second-best use and the first-best use, scalability captures the extent to which the value of the resource in its first-best use declines when it is extended to other uses in addition to the first. To illustrate, consider two cases: (1) The value of a brand used in business A is $100 million, and when applied to business B, it generates $80 million in value in business B, without lowering the value it produces in business A or (2) the value of the brand declines to $100 million in business A, as it is applied in business B, possibly due to brand conflict or dilution. In the first case, the resource is scale-free but not in the second.

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