Journal of Management Inquiry
2023, Vol. 32(1) 21–34

DOI: 10.1177/10564926221127852
journals.sagepub.com/home/jmi
SAGE

Organizational Trust in the Age of the Fourth Industrial Revolution: Shifts in the Form, Production, and Targets of Trust

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Abstract

In this essay, we argue that the advent of the Fourth Industrial Revolution calls for a reexamination of trust patterns within and across organizations. We identify fundamental changes in terms of (1) what form organizational trust takes, (2) how it is produced, and (3) who needs to be trusted. First, and most broadly, trust is likely to become more impersonal and systemic. Trust between actors is increasingly substituted by trust in a system based on digital technology. Second, in terms of trust production modes, characteristic- and institution-based trust production will gain in importance. Third, despite the move toward system trust, there will nonetheless be a need to trust certain individuals; however, these trustees are no longer the counterparts to the interaction but rather third parties in charge of the technological systems and data. Thus, the focal targets of interpersonal trust are changing.

Keywords

trust, digitalization, collaboration, technological innovation, research agenda

> One should expect trust to be increasingly in demand as a means of enduring the complexity of the future which technology will generate (Luhmann, 1979, p. 16).

Introduction

Trust, commonly defined as "the willingness of a party to be vulnerable to the actions of another party" (Mayer et al., 1995, p. 712), is at the heart of virtually all organizational interactions and has consequently attracted substantial interest from management scholars (see Fulmer & Gelfand, 2012; Vanneste et al., 2014, for reviews). Both within and across organizations, trust is an important facilitator of collaboration that can increase the effectiveness of formal and informal transactions (Cook & Schilke, 2010; Graebner et al., 2020). However, trust is highly dynamic and fundamentally affected by broad technological changes and societal trends (Putnam, 2000), making it critical for scholars to stay abreast of relevant developments and scrutinize the ways in which these trends may disrupt how trust operates (Zucker, 1986).

One such noteworthy disruption we are currently witnessing is the Fourth Industrial Revolution (also known as Industry 4.0; hereinafter the 4th IR). Some of the technological advancements of the 4th IR differ substantially from earlier technologies, especially in terms of the capacity to make autonomous decisions and act "smartly" (Murray et al., 2021), which has led to significant structural changes in organizational interactions (Iansiti & Lakhani, 2020). Both general-interest media (e.g., Columbus, 2019) and academics (e.g., Beck et al., 2016; Glaser, 2017) have argued that these new technologies will make organizational trust obsolete.

This essay aims to go beyond broad claims regarding the overall importance of trust to analyze the implications of the 4th IR for trust in greater detail. Rather than rendering trust irrelevant, we contend that the 4th IR requires a fundamental reassessment of *what* form organizational trust takes, *how* it is produced, and *who* needs to be trusted. Virtually by definition, the 4th IR is transforming economic life (e.g., Maynard, 2015; Schwab, 2017). It is thus important for organizational scholars and decision makers to develop an informed opinion of how specifically the 4th IR affects trust patterns within and across organizations.

In the sections that follow, we first offer an overview of some of the key features of the 4th IR and then advance three important ways in which the 4th IR may fundamentally

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transform organizational trust. For the sake of clarity, our major argument is not that the definition of trust needs to change but rather that the 4th IR alters the form of trust and its manifestations. First, in terms of its form, we expect trust to become more impersonal and system based. Second, in terms of its production, we anticipate that process-based modes will lose out to characteristic- and institution-based modes of trust production. Third, in terms of the target of trust, we draw attention to the increasing need to trust the actors in charge of technological systems and data rather than one's direct counterpart in a transaction. We conclude by discussing the wide-ranging implications of these changes, including the decline in the human agency in making trust decisions, new patterns of trust evolution, the growing relevance of swift trust, the difficulties of repairing broken trust, and the increasing incomprehensibility of managerial decision processes. We specifically discuss how these changes open new conversations for a broad range of management areas.

Conceptual Foundations of Organizational Trust

Trust has been at the center of management and organizational scholarship for decades (Deutsch, 1958; Kramer, 1999; McAllister, 1995; Rotter, 1967; for recent reviews see de Jong et al., 2017; Dirks & de Jong, 2022). In past discussions, trust has been conceptualized and operationalized in different ways (Dirks & Ferrin, 2002) and at times conflated with related constructs, such as confidence and predictability. Scholars have thus devoted much attention to clarifying the ontology of trust, especially during the 1990s, when a stream of important and impactful works on the meaning of trust emerged (e.g., Das & Teng, 1998; Lewicki et al., 1998; Lewicki & Bunker, 1996; Mayer et al., 1995; Rousseau et al., 1998). Among the various conceptualizations of trust, dependence on other entities and willingness to be vulnerable and to take risks are among the most commonly recognized definitional components (Schilke et al., 2021). Vulnerability and risk are particularly central to understanding trust (Mayer & Davis, 1999). In Mayer et al.'s (1995) definition of trust, the defining feature is that "risk must be recognized and assumed" (p. 714) for trust to be distinguished from confidence or predictability. In terms of its sources, trust is based on both the trustor's trust propensity (i.e., a dispositional willingness to rely on others) and the trustor's evaluations of the trustworthiness of the trustee (Colquitt et al., 2007). These trustworthiness evaluations can, in turn, be based on different types of cues, such as relationship history, social categories, and the institutional environment (Zucker, 1986).

Control is another construct that has been discussed extensively in the context of trust (e.g., Bijlsma-Frankema & Costa, 2005; Cao & Lumineau, 2015; Long & Sitkin, 2018; Long & Weibel, 2018). Agency theorists view control mechanisms (e.g., monitoring and incentives) as useful instruments for the principal to constrain agents' behaviors, align their interests, and reduce risks. Control and trust have thus sometimes been viewed as two alternative mechanisms for facilitating cooperation between the two parties (Das & Teng, 1998; Mayer et al., 1995). The more recent literature on the interrelationship between the two constructs notes that, in most settings, these two mechanisms are not mutually exclusive and therefore do not operate as pure alternatives. It is thus important to analyze trust as a distinct conceptual mechanism supporting the principal-agent relationship. The debate around the relationship between control and trust also suggests that there can be a strong complementary (rather than substitutive) effect between the two (see Cao & Lumineau, 2015 for a review). In other words, enhanced control can form a basis for higher trust (e.g., Lumineau, 2017; Poppo & Zenger, 2002; Vlaar et al., 2007).

Although trust plays a central role in many organizational interactions, the literature on trust contingencies (e.g., Atuahene-Gima & Li, 2002; Krishnan et al., 2006; Luo, 2002) notes that the relative importance of trust varies across settings. Trust, almost by definition, is more relevant when people are dependent on another entity's performance and there is higher uncertainty regarding whether that entity can successfully perform the task at hand (Mayer et al., 1995; McKnight et al., 1998). Two sources of limitations in human nature explain such uncertainty—*opportunism* and *bounded rationality* (Simon, 1957; Williamson, 1985). Trust is more relevant in transactions that have more room for opportunistic behaviors and/or whenever it is difficult for the principal to predict the performance of the agent.

One such condition that exacerbates the hazards of both opportunism and bounded rationality, and thus can make trust more relevant, is high levels of information asymmetry (i.e., imperfect access to information by different parties to a transaction). While conceptually distinct, information asymmetry can be a direct antecedent of both opportunism and bounded rationality. High levels of information asymmetry give the agent more opportunities to engage in opportunistic behaviors (Williamson, 1975). In addition, asymmetric information about the competence of the agent makes it difficult for the principal to predict the agent's performance (Schilke et al., 2017). Both aspects lead to higher uncertainty regarding the agent's behavior, and the principal needs to decide whether they are willing to make themselves vulnerable to (i.e., trust) the agent. Although information asymmetry is a pervasive phenomenon, it is more salient in some situations than others. A case in point are highly intermediated industries, where centralized operators (such as Amazon and Facebook) have the power to aggregate information and enjoy an information advantage.

Finally, we note that the relationship between information technology and trust has attracted much scholarly interest. Scholars have pointed out that technologies may shape trusting behaviors among economic actors (e.g., Ba & Pavlou, 2002; Karunakaran, 2022). At the same time, trust in technologies is also essential for new technology adoption and diffusion (e.g., Müller et al., 2018; Shestakofsky, 2017). In this essay, we both complement and extend the line of inquiry at the intersection of trust and technology by critically assessing how the current wave of digital transformation may substantially alter the dynamics of organizational trust. In the next section, we elaborate on some of the unique changes the 4th IR brings to organizational processes, which helps us set the stage for analyzing the implications of these trends specifically for organizational trust.

Features of the 4th IR

The 4th IR is a sequel to three previous historical eras of particularly intense technological advancement. The 1st IR began at the end of the 18th century when mechanical production based on water and steam power started to proliferate; the 2nd IR occurred at the beginning of the 20th century with the arrival of mass production based on electrical energy; the 3rd IR started in the 1970s with dramatically increased automatic production based on electronics and internet technology; and the 4th IR is currently under way, with the proliferation of autonomous systems that enable a convergence of computation, networking, and physical processes. The 4th IR is distinct from previous developments because it leverages entirely new generations of technology that enable high levels of interconnectivity and interoperability among humans and machines (Jazdi, 2014).

At the core of the 4th IR is an unprecedented degree of digitization across all industries (Schwab, 2017), which is enabled by a set of path-breaking technologies, such as blockchain, the Internet of Things (IoT), cloud computing, and machine learning (Sturgeon, 2021; Xu et al., 2018). Although each of these technologies has unique features, they share important similarities related to interconnectivity and interoperability. In this essay, we will focus on this common ground. We concur with recent calls by Bailey et al. (2022) and Burrell and Fourcade (2021) to treat technologies not merely as background contexts for organizational actions but rather as interwoven relational mechanisms that shape human associations, organizational processes, and social structures. In line with this viewpoint, we suggest that the backbone technologies of the 4th IR give rise to several interdependent trends pertaining to how economic actors organize, of which we will highlight four: pervasive reliance on data, computerization of intelligence, automation, and decentralization.

The first development pertains to an explosion of the volume, variety, and velocity of *data* being analyzed in today's economy (Kellogg et al., 2020). Many physical devices, such as smart sensors, are now collecting information around the clock and transmitting it to computer systems (Lee et al., 2014). Much information that was previously neglected is now captured, digitized, and incorporated as inputs for organizational systems (Adner et al., 2019; Schafheitle et al., 2020). Examples range from online footprints to social connections, locations, and facial recognition of employees (Richards & King, 2014). Data are being uploaded, transmitted, and analyzed in a nearly real-time manner to support organizational decision-making (Kellogg et al., 2020). In the 4th IR, data have gained unprecedented relevance for the functioning of organizations and the economy as a whole.

Analyzing all these data calls for computationally powerful machines that can assist or even replace human agents. Ongoing advances in artificial intelligence, such as neural networks and deep learning approaches, provide the basis for unprecedented *computerization of intelligence*, which enables machines to execute increasingly sophisticated tasks. Perhaps most notably, machine learning techniques are now routinely used to train technology to learn from experience and perform a variety of key tasks ranging from categorization to prediction (Hull, 2020). For example, venture capitalists are implementing artificial intelligence technologies to support their screening and decision-making (Corea, 2019). Artificial intelligence differs from traditional generations of technology in that it allows for increasingly autonomous decisions that go beyond the limited knowledge of programmers (Glikson & Woolley, 2020; Iansiti & Lakhani, 2020).

As a result of growing computing capabilities and the increasing diffusion of artificial intelligence, economic activities tend to be executed increasingly *automatically*. Information collected by smart sensors and mobile devices can be automatically uploaded to the cloud, and a large portion of routinized decision-making tasks can be taken over by prescribed algorithms (Adner et al., 2019). At the same time, machines can feed information about task performance to systems to support the automatic control of production activities. For instance, business transactions can be executed automatically via blockchain-powered smart contracts (preprogrammed codes that are automatically executed once certain prescribed conditions are met) (Lumineau et al., 2021). Differing from the 3rd IR, automation in the 4th IR moves beyond the confines of organizational boundaries and occurs *across* organizations (Schwab, 2017), such as in supply chains or among alliance partners.

To facilitate such automated, fast, and flexible adaptations, the structure for organizing economic activities is becoming more *decentralized*. Smart devices are able to exchange information directly with one another (Moeuf et al., 2018), long-distance collaboration is becoming increasingly prevalent (Enkel & Heil, 2014), and the rise of decentralized autonomous organizations challenges traditional hierarchical organizational forms (Hsieh & Vergne, forthcoming; Hsieh et al., 2018; Seidel, 2018). In sum, communication and collaboration between individual entities have become less effortful, opening the door for decision-making to become less hierarchical.

All of these trends make it clear that the 4th IR fundamentally alters how employees and organizations interact. As a result, it is relevant to examine when and how to trust, as a critical component of social interactions among organizational actors, might be affected by these changes. Returning to the contingencies of trust discussed in the previous section, we suggest that the 4th IR will have particularly profound implications for trust when it affects opportunism and bounded rationality in transactions. Specifically, we suggest two conditions under which the 4th IR is likely to have important consequences for trust: (1) when technologies, instead of human entities, mediate transactions and (2) when there is a larger amount of information available for the computational prediction of the trustee's trustworthiness. The first condition relates to the trends of automation and decentralization in the 4th IR, which constrain chances for human agents to exhibit opportunistic behaviors. The second condition relates to big data and artificial intelligence. The availability of more detailed information about the trustee, along with the superior analytical capabilities of algorithms, helps compensate for the bounded rationality of the trustor in evaluating the trustworthiness of the trustee. Based on these conditions, we suggest that the 4th IR converts the forms and manifestations of organizational trust in several significant, interrelated ways. We next elaborate on how the advent of the 4th IR alters *what* form trust takes, *how* trust is produced, and *who* needs to be trusted.

A Shift in the Form of Trust

While the 4th IR may help facilitate collaborations both within and across organizations, we suggest that it also involves a substantial reshaping of these collaborations. Rather than human agents dealing with other human agents directly, the technologies supporting the 4th IR *mediate* collaboration. This contrasts with conventional collaboration structures in which the identity of the other party serves as a focal point when initiating or sustaining a trusting relationship (Schilke & Cook, 2013). Most notably, a shared history or a party's general reputation has traditionally served to back expectations of the partner's behaviors and build confidence regarding the partner's trustworthiness based on past experience or ongoing interactions.

In contrast, with the advent of the 4th IR, such direct connections are no longer necessarily needed. An increasing number of tasks can be executed quasi-automatically following instructions given by intelligent systems, obviating the need for human intervention in carrying out the transaction (Hofmann et al., 2019). The agency of human actors is thus increasingly crowded out by technological processes, with the decision of whether and whom to trust falling within the competence of the system. However, we disagree with the growing notion that the technologies of the 4th IR are entirely "trustless" (e.g., Beck et al., 2016; Glaser, 2017). Rather than the 4th IR making trust irrelevant, we suggest that trust continues to play a vital role in organizational interactions. However—and this is important—the form of trust changes as collaboration becomes structured through new technologies. Following Luhmann (1979) and Lewis and Weigert (1985), we distinguish between personal trust and system trust (see also Lane & Bachmann, 1998; Shapiro, 1987 for similar distinctions). Whereas personal trust involves a direct bond between individuals, system trust is placed within the functioning of a social system. Following the lead of Trist et al. (1963), we extend the classic notion of a system to refer to not only social systems but also technological systems. Broadly, a system refers to any impersonal structure that mediates the transactional relationships between actors (Pennington et al., 2003). This understanding is consistent with the field of information systems research, which employs the term system trust to denote reliance on the functionality of information systems, such as e-commerce platforms and virtual communities (e.g., de Vries et al., 2003; Hsu et al., 2011; Lankton et al., 2015). Instead of trusting the integrity, competence, and benevolence of individuals, actors now need to trust the reliability, functionality, and usefulness of the system to perform the task at hand (McKnight et al., 2011). Thus, we suggest that with the 4th IR, system trust becomes increasingly important, with serious implications for the levels of analysis involved in trusting relationships and, most notably, the roles of individuals and collective systems (Lumineau & Schilke, 2018).

A case in point is the rising importance of blockchain in organizing collaborations in the 4th IR (Fernández-Caramés & Fraga-Lamas, 2019; Seidel & Greve, 2017; Viriyasitavat et al., 2020; Wang et al., 2022). Blockchain—a cryptography-based decentralized system consisting of an ongoing list of digital records—is often regarded as one of the most disruptive recent technological innovations (e.g., Lumineau et al., 2021). Blockchain enables decentralized decision-making through certain consensus mechanisms such that no single centralized party holds full discretion in updating the shared information.[1] In this system, people trust the information they receive without the need for interpersonal trust in other participants (Seidel, 2018). In addition, blockchain-powered smart contracts support the autonomous execution of agreements, thereby limiting human interference. Blockchain thus relies on codes and programs to automatically reject deviant behaviors and enforce only acceptable actions. Managers may use blockchain to constrain the behaviors of other actors, including subordinates, suppliers, or customers. This control effect represents a fundamental departure from actors' reliance on personal trust in most traditional collaborations. In these types of settings, the object of trust shifts from the individual to the system level.

Trustors are now taking risks by making themselves vulnerable to the reliability, functionality, and usefulness of the system in performing the job (McKnight et al., 2011). They trust the whole system powered by algorithms to ensure the integrity of the information and transactions.

A Shift in the Modes of Trust Production

Of course, not all 4th IR technologies mediate transactions, and not all transactions are mediated by automated technologies. As a result, personal trust will likely continue to play an important (albeit attenuated) role in economic exchanges. For those transactions that still rely on personal trust, the 4th IR is triggering a shift in the modes of trust production—that is, in how trust is developed. Next, we turn to the production of personal trust.

In her seminal article, Zucker (1986) identifies three distinct modes of trust production[2]: (1) process-based, where trust is tied to past or expected exchanges between the collaborating parties; (2) characteristic-based, where trust is tied to characteristics such as belonging to a certain social category; and (3) institution-based, where trust is tied to formal societal structures. While these three approaches comprehensively cover the social origins of trust, the specific importance of each is highly context dependent and historically contingent, such that different trust production modes are more relevant than others under specific circumstances (Schilke et al., 2017).

For collaborations organized in the 4th IR, we suggest that in relative terms, process-based trust production gives way to characteristic- and institution-based trust production. Process-based trust production comes from first-hand collaborative experience with a particular partner (Lumineau et al., 2011; Schilke et al., 2013). However, as noted above, the history of and ties to specific actors become comparatively less relevant when new technologies intermediate interactions. Many of these technologies rely on a set of protocols and codes that determine the trustworthiness of a prospective partner not based on past interactions but through categorization—which is at the core of the notion of characteristic-based trust production. In characteristic-based trust production, information concerning social similarity with a categorical archetype is the key signal of trustworthiness. That is, if the category to which a trustee belongs is considered trustworthy, the trustee will also be considered trustworthy. As such, the type of information on which trust decisions are based is shifting from historical and interpersonal experiences to data that allow for categorizing an actor along meaningful dimensions that are predictive of trustworthiness.

To offer an example, machine learning algorithms are increasingly used to model and quantify trust in a variety of organizational fields ranging from insurance companies such as GEICO, which offers customized products to applicants based on their background information (Bean, 2018), to e-commerce providers weeding out fake reviewers (Elmurngi & Gherbi, 2017). Generally, machine learning aims to automatically detect complex patterns and make predictions by leveraging large datasets. Applied to trust decisions, many machine learning algorithms ascribe trust scores to learned classes of actors, generalizing experiences as social categories and applying those categories when forming trustworthiness evaluations (Burnett et al., 2013). In other words, trust is based on computational calculations that leverage data-based stereotypes about the groups to which the trustee belongs. For instance, in determining the trustworthiness of a seller at an auction, relevant predictive features may include the product category, price, and the number of items already sold by the seller. Building on historical data, a linear classifier is obtained to estimate whether a particular seller is similar to those that have already proved trustworthy (Liu et al., 2014). The ultimate trust decision is based not on the collaborative history between two parties but on a more stereotypical categorization.

Notably, the specific mechanisms underlying Zucker's (1986) characteristic-based trust production can be further distinguished into two types—homophily and categorization (Schilke et al., 2021). First, the homophily mechanism refers to trust as a result of high social similarity between the trustor and trustee, given that humans are known to trust others when they observe their counterparts to have characteristics similar to their own. Second, characteristic-based trust production can also stem from social categorization independent of similarity. That is, certain members of social categories are considered trustworthy regardless of whether trustor–trustee similarity is high. In these cases, the correspondence of the trustee with the *archetype of the category*, not similarity with the trustor, is what matters (McKnight et al., 1998). This second form of categorical trust production comes to the fore and explains much of the characteristic-based trust production in the context of the 4th IR, whereas homophily may in fact play a lesser role.

In addition to being characteristic based, the trust created through technological systems associated with the 4th IR can be viewed as a form of institution-based trust, which is often considered the most important type of trust in business situations where collaborators lack familiarity with each other (Jarvenpaa & Teigland, 2017).[3] In this mode of trust production, formal mechanisms provide trust that rests neither on a history of exchange (as in process-based trust production) nor on the trustee's characteristics (as in characteristic-based trust production). These formal mechanisms establish unambiguous and specific expectations for exchange and guarantee that the transaction will take place as promised. While institution-based trust production has thrived since the early stages of industrialization, the automation and further distribution of trust brought about by the technologies of the 4th IR further amplify the role of institution-based trust production. Instead of relying on enforcement through interpersonal means, the technologies of the 4th IR rely on a set of protocols and code-based rules. As a result, trust is strongly "embedded in the institutional environment in which a relationship is placed, building on favourable assumptions about the trustee's future behaviour vis-à-vis such conditions" (Bachmann & Inkpen, 2011, p. 284).

Finally, it is worth noting that the 4th IR certainly does not preclude process-based trust production and that the shift in the importance of different trust production modes should be understood in relative terms. Indeed, 4th IR technologies such as blockchain may even support process-based trust production by (immutably) recording the historical data of prior relationships between two parties, allowing transaction partners to retrieve historical transaction data and use them to predict their partner's future behavior. However, a much more salient trend associated with the 4th IR is the proliferation of data about one particular party that are publicly available even to actors who had no prior relationship with that party, along with techniques to comprehensively analyze such public data (Glikson & Woolley, 2020; Kellogg et al., 2020). As a result, characteristic-based trust is becoming even more relevant than before—it is less important to have had first-hand experience with a party to assess their trustworthiness. Moreover, 4th IR technologies such as blockchain create code-based rules that underlie institution-based trust. In the context of these two modes of trust production, the transactional history between two parties becomes less critical. Even without prior relationship experience, the trustor can make informed trust decisions thanks to 4th IR technologies.

A Shift in the Targets of Trust

A third proposed shift associated with the 4th IR relates to a change in the salient targets of trust. Even though the importance of trusting individuals has decreased with the dawning of the 4th IR, there will nonetheless always be a need to trust *certain* people or entities. As Lewis and Weigert (1985, p. 983) note, "system trust ultimately depends on personal trust." However, these actors are no longer exclusively the counterparts to a collaboration but rather third parties in charge of developing and maintaining digital systems, such as developer engineers and companies providing technological infrastructure. At least for the time being, human involvement remains essential to design technological systems and algorithmic technologies that function correctly, which is why system users are vulnerable to these individuals. Specifically, trustors face considerable uncertainty regarding (1) who designed the system, (2) who provides the information that feeds the algorithms, and (3) who has access to the data.

First, machine intelligence is logical and optimal in the sense that it strictly follows the instructions programmed by the system designers. Automated trusting decisions are necessarily based on a set of preconceived notions to draw inferences. However, it is possible that a coder or system architect may have introduced—intentionally or not—cultural and/or personal biases into the code supporting the technology. As algorithms support increasingly characteristic-based trust decision-making, they may be based on (conscious or unconscious) clichés (e.g., trust women below 25, do not trust French people with a PhD). Examples of such potentially prejudiced decisions abound, from Google's allegedly racist image labeling (Barr, 2015) to Amazon's purportedly gender-biased recruiting (Dastin, 2018). Thus, reliance on system trust often comes with much uncertainty regarding who designed the system and their underlying incentives and motivations.

The second target of trust that is increasingly relevant in the 4th IR are the individuals and organizations providing the information that feeds the algorithms. The "garbage in, garbage out" problem associated with data analytics means that inaccurate inputs will necessarily produce faulty outputs. Bad input may originate from purposive or unpurposive mistakes ranging from topology errors to malicious attacks (Huang et al., 2013). For example, machine learning depends on both historical data to train the model and new data to make predictions, and biased data from unreliable sources can result in incorrect conclusions (Redman, 2018). Similarly, the execution of smart contracts often relies on gateways providing information about the state of the world (Halaburda, 2018). Therefore, trust in the parties providing data feeds is a critical factor in the use of technological systems.

Third, the advent of the 4th IR warrants trust in data holders—the entities that aggregate, analyze, and profit from the information they control. Much of the data people share is based on the trusting expectation that these data will be kept confidential and gathered only with consent (van der Werff et al., 2021). However, in reality, a great deal of sensitive information is collected without consent and employed for a variety of purposes, and trustors often have a very limited understanding of how these data are used. The Facebook–Cambridge Analytica data scandal (Confessore, 2018) illustrates a recent unethical exploitation of the centralization of information in a limited number of powerful organizations. In 2018, Cambridge Analytica, a political data company, was reported to have secured access to the personal information of over 50 million Facebook users. The data were used to support advertisements for the U.S. presidential election by providing analytics about the personal characteristics and behaviors of U.S. voters. The scandal raised significant concerns regarding information privacy and the influence of giant internet companies in the digital age.

Opening a New Conversation for Management Scholars

Addressing the economic impact of the 4th IR, the World Economic Forum (2020) observed that "the speed, breadth and depth of this revolution is forcing us to rethink how countries develop, how organisations create value and even what it means to be human." The key argument of our essay is that these wide-ranging implications of the 4th IR are affecting several key aspects of organizational trust both within and across organizations. We propose that trust will continue to be central in organizational interactions, albeit in fundamentally different ways. The 4th IR is not only foregrounding system trust but also leading to a decline in the relative relevance of process-based trust production while bringing to the fore new targets of trust, such as developers, the entities providing information feeds, and data holders. Indeed, many of the changes proposed here call for a reevaluation of a wide variety of key issues that are at the heart of management scholarship. Next, we discuss some of the far-ranging implications of these changes not only for trust scholars but also for many other streams of research in management (see Table 1 for a summary).

Shift in the Form of Trust

One critical implication of the shift in the form of trust is that trustors may lose some of their agency regarding whether and whom to trust. With the rise of the 4th IR, computers are increasingly defining what humans should do and which behaviors are deemed trustworthy (Iansiti & Lakhani, 2020). In the banking industry, for example, bankers have traditionally been in charge of assessing the profile of a potential borrower to determine whether he or she can be trusted to pay off the loan on time. Based on a number of lending criteria and a history of prior transactions with the client, a banker in the past would have individually interpreted each situation and may have interviewed the loan applicant to determine his or her eligibility and potential payment plans (Guseva & Rona-Tas, 2001). This traditional approach sharply contrasts with, for instance, Ant Financial's MYbank (Bloomberg News, 2019), which relies on an entirely digital loan approval process. The application takes only 3 min and a few taps on a smartphone, and it does not involve any human bankers. This example illustrates how organizations' decisions on whether and whom to trust are moving within the purview of software that automates many processes traditionally carried out by humans.

We see manifold opportunities for scholars working in different management areas to further explore the influence of this agency shift on important organizational processes and outcomes. This shift invites scholars in information systems to pay greater attention to the way technologies take over some of humans' agency in developing rules (i.e., *how* to do something), selecting actions (i.e., *what* to do), or both. For example, deep learning techniques allow technology to learn from large-scale unstructured data without human supervision and generate features that human agents often do not fully understand (Goodfellow et al., 2016). These features are used as rules to make decisions with minimal human interference (e.g., fraud detection and facial recognition). At the same time, smart contracts

Table 1. A Summary of Implications and Future Research Opportunities.

Theme	Implications	Examples of research questions
Shift in the form of trust	Trustors may lose some of their agency in making trust decisions	How may the shift in agency in trust decisions impact organizational processes (e.g., developing rules)?
		How may the shift in agency in trust decisions impact organizational structure (e.g., division of labor, power distribution, and decision processes)?
		How may the shift in agency in trust decisions impact human resource management practices within organizations?
	Trust may follow different dynamics over time	How do trust trajectories differ between personal trust and system trust?
		How do trust breach and repair practices differ between personal trust and system trust?
Shift in the modes of trust production	Organizations' approaches for being perceived as trustworthy (and the competitive advantage associated with it) may change	How can organizations improve their perceived trustworthiness among relevant stakeholders in the new era?
	Swift trust and calculative trust may increase in importance	How may the validity of traditional collaborative strategies (e.g., contractual designs and repeated ties) change in the new era?
	Organizations may face new challenges in managing trust decisions	How can organizations better improve their understanding and monitoring of trust decisions in the new era?
Shift in the targets of trust	Actors may need to trust others that they have never met	How can actors determine the trustworthiness of unfamiliar and distant parties?
		How can trust in unfamiliar and distant trustees be repaired?

empowered by blockchain execute actions only when certain conditions are met and do so without human involvement. By opting for smart contracts, human agents deliberately relinquish their agency and delegate actions to technologies. Such changes in the locus of agency may in turn affect the degree and predictability of organizational change and the responsiveness of organizational routines (Murray et al., 2021).

Despite the increasing efficiency that follows, this transfer of agency may entail significant downsides, sometimes referred to as the "automation paradox," which could be of particular interest to business ethics scholars. When individuals reach the point of overtrusting the system, accidents such as the Air France Flight 447 crash (Charette, 2012) or self-driving Uber car accidents (McCausland, 2019) may occur. In addition, this shift has important implications for research on organizational behavior because a loss of agency may create a sense of alienation from decisions, ultimately leading to anxiety among organizational members (Schneider & Sting, 2020). This shift should also encourage organization design scholars to reexamine key aspects of organizational structure, such as the division of labor, power distribution, and decision processes (Miller et al., 2009; Simon, 1973). Furthermore, this shift urges scholars in human resource management to reconsider, for example, which group of employees (e.g., IT personnel versus frontline workers) possesses more firm-specific knowledge and creates more value, which would provide human resource managers with new monitoring and incentivizing mechanisms.

The shift from personal to system trust also creates significant changes in trust dynamics over time—a central topic in contemporary trust scholarship (e.g., Faems et al., 2008). An important but unresolved question pertains to the specific trajectory of trust development. While some scholars suggest that personal trust will be low at the beginning of a relationship (e.g., Zand, 1972), others argue that initial trust could in fact be relatively high under specific conditions (e.g., depending on the ambiguity of the situation, McKnight et al., 1998). However, the patterns observed for personal trust may no longer hold as system trust gains relevance. In general, trust in technological systems tends to be remarkably high when people first adopt a technology but may gradually decrease with more extensive use (Glikson & Woolley, 2020). In other words, at the beginning of an interaction, people may undertrust other people but overtrust systems.

Moreover, trust breaches may have significantly different implications for system trust than for personal trust. Some of the mechanisms of trust breach and repair are not readily transferable from interpersonal transgressions to system-level failures (Gillespie & Dietz, 2009). One reason for this lack of transferability is that there are usually more contributors to system-level failures than to interpersonal failures. As a result, responsibilities tend to be more distant and diffuse, leading to ambiguity regarding the real cause of the failure and the identity of the persons responsible for the trust breach. Such ambiguity also creates significant hurdles for trust repair. For example, after Wells Fargo's scandal involving the arbitrary creation of millions of fraudulent bank accounts without the individuals' consent was revealed, there was no consensus on who should be held accountable (Hurley & Hurley, 2020). The targets of blame included individual branch workers, top managers, and the culture of the organization. The causal ambiguity of the event resulted in a vague understanding of the scandal and made it difficult for Wells Fargo to repair trust in the company.

In addition, system trust breaches can be more wide-reaching, as they affect not only a focal relationship between two parties but also many other interactions facilitated by the system. In the age of enhanced automation, objective technologies and algorithms aid the enforcement of agreements, with fewer human actors involved. As a result, there are fewer opportunities for human actors to violate the norms set forth in an agreement and the expectations of their partners. In this way, trust becomes more difficult to breach in the first place. However, once a trust breach has occurred, the consequences can be wide-ranging, influencing not just one but many collaborations taking place in the system. The complexity of the technological systems in the 4th IR makes trust repair even more problematic in terms of the difficulty of juggling a speedy response and an effective settlement. Such changes have important implications, particularly for scholars working on control and governance issues in both intra- and interorganizational contexts. These scholars could, for instance, analyze how this set of changes affects the joint use of formal and informal governance systems and the interplay between them (Poppo & Zenger, 2002). In particular, the interplay between trust and control has received much attention (Long & Sitkin, 2018), and recent research points to the importance of contingency factors (Cao & Lumineau, 2015). It would therefore be interesting to assess how new trends brought about by the 4th IR may affect the complementary versus substitutive nature of trust and control.

Shift in the Modes of Trust Production

In addition to these issues related to the shift from personal to system trust, the changes in the modes of trust production have significant implications for organizations and management scholarship. Trustworthiness is commonly considered an important organizational resource that can constitute a source of competitive advantage (Barney & Hansen, 1994; Schilke & Cook, 2015). As a result, it is important for strategy scholars to understand how organizations can improve their perceived trustworthiness among relevant stakeholders in the new era. The 4th IR certainly does not nullify the importance of traditional relationship management, but traditional process-based approaches need to be complemented with a deeper understanding of the data and algorithms that determine how trustworthiness decisions are made.

The shifts in the modes of trust production also call for more research on swift trust. Swift trust, also called initial trust, is developed prior to an interaction or upon the very first encounter and thus differs from trust developed through interactions (Meyerson et al., 1996; Robert et al., 2009). Research suggests that swift trust tends to be formed based on second-hand knowledge (such as reputation) and derives from social categorizations and institutions (e.g., McKnight et al., 1998; McKnight & Chervany, 2006). Thus, earlier studies suggest that swift trust is often based on characteristics or institutions rather than processes (Blomqvist & Cook, 2018; Schilke & Huang, 2018). By changing the production modes of trust, the 4th IR increases the importance of swift trust through enhanced categorization and consolidated code-based institutions.

To return to our earlier discussion of machine learning applying a logic of characteristic-based trust production, such machine-based intelligence has the capacity to provide more complex and precise predictions than a human mind because it can leverage a very large volume of data and high computational power. However, algorithms merely follow well-defined rules of action and do not leave room for emotions. While both interpersonal and interorganizational trust often involve a mix of rational calculations based on a cost–benefit analysis determined by both economic reasoning and more intuitive and emotional components (Kramer, 1999; Lumineau, 2017), this shift toward characteristic-based trust production implies a focus on calculative-based trust, potentially taking away some of the unique human skills that help discriminate trustworthy targets from untrustworthy ones (Schilke & Huang, 2018). These changes call for revisiting firms' strategic choices in interorganizational relationships, such as the structural arrangements that build upon the interactive patterns formed between contractual framings and trusting behaviors (e.g., Lumineau, 2017).

At the same time, the shift to characteristic-based and institution-based trust production gives rise to new issues. The comprehensibility of the underlying algorithms and the ability of individuals to act independently are often questionable. If systems operate as "black boxes," ill-meaning individuals may manipulate the system to their advantage, and this manipulation may go unnoticed (Nassar et al., 2020). Another potential problem relates to the lack of transparency and replicability of technologies relying on artificial intelligence. For example, because of the inherent computational complexity and causal ambiguity involved in these technologies, most people (sometimes even the code developers themselves) do not understand the process or the outputs from machine learning. As observed by Glikson and Woolley (2020, p. 6), "the complex multilayer process of AI decision making is generally not transparent. This means that AI's decisions could be difficult to predict, and the logic behind each decision made is often poorly understood." In addition, technologies are often not deterministic in the sense that some decisions are not necessarily replicable. This lack of replicability and lack of understanding of the inner operating rules make it difficult to assess the fairness of trusting decisions. For example, it is harder to determine whether the trustworthiness evaluation process contains biases or discrimination embedded in the algorithms, either on purpose or by accident. Such changes then give rise to new issues in circumstances where knowledge of the mechanisms underlying decision-making is inherently ambiguous. For example, the ability of organizations to monitor how and why they make certain decisions may become a new source of competitive advantage. This new context also calls for new paradigms of leadership to be developed to guide people through uncertainties and ambiguity (Bolden & O'Regan, 2016).

Shift in the Target of Trust

The shift in the target of trust implies that people now have to trust others that they have never met—including developers, entities providing information feeds, and data holders. This again challenges traditional practices of trust building because there is typically little familiarity and no direct interaction between trustors and these types of trust targets (e.g., Ba & Pavlou, 2002). In this context, how can actors determine the trustworthiness—in terms of both goodwill and competence—of these distant parties? The literature on swift trust may provide a useful starting point to address this question (e.g., McKnight & Chervany, 2006; Robert et al., 2009; Schilke & Huang, 2018). For example, McKnight et al. (1998) argue that reputation inference, social categorization, and illusions of control may help form initial trust in unknown targets. Moreover, signaling theory (Spence, 1973) may allow researchers to take the viewpoint of these distant trustees and understand what types of credible signals they can send that untrustworthy counterparts cannot easily employ. Such a shift also brings up new issues for identity management in a digitalized world, such as how actors build their identities with distant stakeholders and maintains their boundaries (Bange et al., 2022).

It is also important to study the role of these distant trustees in trust repair after a system failure. The unfamiliarity and lack of interaction with these new targets of trust may make it difficult to engage in typical trust-repair processes such as developing shared mental models and deepening relationships, which calls for a new line of research into the repair of system trust. The insights that follow could prove particularly valuable for conflict management scholars interested in understanding the specific roots of organizational conflicts and, in turn, identifying appropriate repair strategies (Lewicki & Wiethoff, 2000).

Finally, scholars should pay attention to the endogenous nature of the choice among alternative technologies. Actors may select a specific technology by anticipating its effects on certain types of trust. This brings forth an interesting question about the conditions regarding the trade-off between different technologies as a function of the different types of trust desired.

Conclusion

In this essay, we argue that three shifts in organizational trust patterns brought about by the advent of the 4th IR call for revisiting long-standing positions in the trust literature and generating new issues that require the refinement and reevaluation of existing knowledge in a broad range of management fields. We argue that rather than making trust obsolete, the 4th IR is leading to qualitative changes in trust, making it important for both micro and macro management scholars to reexamine what we think we know about organizational trust. We hope this essay helps stimulate a new stream of scholarly studies for a better understanding of trust and its implications in this exciting new era.

Acknowledgements

Guidance from the editor Pablo Martin de Holan and three anonymous referees is gratefully acknowledged. We are also thankful for the helpful suggestions and comments by Kirsimarja Blomqvist, Darcy Fudge Kamal, Melissa Graebner, Derek Harmon, Rekha Krishnan, Roy Lewicki, Nuno Oliveira, Martin Reimann, Bart Vanneste, Antoinette Weibel, Yangbing Zhang, and Lynne Zucker on earlier versions of this paper. The paper benefitted from discussions with participants of the FINT Virtual Seminar Series. All errors remain the authors' own.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by a grant from the National Science Foundation, Division of Social and Economic Sciences (grant no. 1943688) to the second author. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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Notes

1. Our argument thus shares similarities with Allen et al.'s (2020) idea that blockchain is an "institutional technology" (see also Davidson et al., 2018). These authors suggest that blockchain is an institutional technology because of the distribution of its governance and the way it introduces formal rules. Our arguments converge in that we both suggest that institutional technologies are mechanisms that enable systems of governance for economic exchange.
2. Trust production modes are conceptually distinct from trust itself, in that the former describe the origins of the latter (Pratt et al., 2019; Schilke et al., 2017).
3. The trust literature suggests that system trust is both similar to and conceptually distinct from institution-based trust (Bachmann, 2003; Bachmann & Inkpen, 2011). Following Bachmann (2003), the object of system trust is an abstract system (e.g., cultural, regulatory, or technological systems—Luhmann, 1979), while institution-based trust refers to trust between actors that is based on formal rules embedded in the institutional environment.

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