Artificial Intelligence as an Endogenous Mechanism of Institutional Isomorphism

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Abstract

Emerging technologies equipped with artificial intelligence are improving in their capability to autonomously make decisions on behalf of people and organizations. We argue that organizations' implementation of these AI technologies will perpetuate a new mechanism of isomorphism, through which the work practices of organizations will become increasingly similar over time, which we call *endogenous isomorphism.* Unlike mechanisms of isomorphism that depend on knowledgeable actors' responses to the institutional field, *endogenous isomorphism* occurs as AI technologies implement patterns gleaned from aggregated data across time and space. In this chapter, we draw on organizational theory in the areas of institutional isomorphism, structuration, and organizational change to theorize the endogenous change that the use of AI technologies to autonomously make organizational decisions will contrive. We present an illustrative example of endogenous isomorphism from our research on AI scheduling technologies and discuss the theoretical, practical, and methodological implications of our conceptual argument.

Artificial Intelligence as an Endogenous Mechanism of Institutional Isomorphism

Technology companies are using advances in artificial intelligence to provide businesses and individuals with products that promise to increase workplace productivity and effectiveness (Trapp, 2019). Artificial intelligence, as a set of computational processes designed to mimic human intelligence to make complex decisions (Berente et al., 2021), leverages patterns found in data to learn and improve over time. Across a variety of professional domains, organizations are implementing technologies equipped with artificial intelligence to accomplish work.

Emerging technologies equipped with artificial intelligence are improving in their capabilities to autonomously make decisions on behalf of people and organizations (Berente et al., 2021). AI technologies make decisions by making predictions about which action is most likely to lead to a given desirable outcome across work settings. Though people vary in how they go about their work, AI technologies must appeal to a critical mass of users by making decisions based on patterns. The data that provides these patterns inform decisions made by AI such that actions are selected based on the probability that they will produce a desirable outcome (as defined by developers of machine learning algorithms that make these choices) across use cases.

For AI companies that sell software as a service (SaaS), the business case for their tools lies in their ability to improve the computing abilities of their technologies over time. To make the case for the viability of their product, companies selling software powered by artificial intelligence must demonstrate that their products will produce a return on investment for users that outweighs the cost of switching and learning services (Davenport et al.; 2018). Many technology companies champion the power of big data and predictive analytics to distinguish the value of their AI solution. This approach allows them to appeal to clients at scale and to increase the gross margins of their business (Casado & Bornstein, 2020). It is in companies' best interest to help the machine learning algorithms that power their AI tools improve and to leverage vast amounts of aggregated data gathered across all users. Thus, the sophistication of these tools depends on their ability to account for as many use cases as possible.

How AI technologies are designed to learn presents a potential challenge for the organizations that use these tools. Though organizational leadership may make decisions based on what action is most appropriate for their specific organization or particular industry, most emerging AI technologies do not have sufficient data for a level of customization that would match this process. In choosing to adopt AI technologies that make decisions about organizational practices, organizations may intentionally or unintentionally implement work practices that are appropriate for the average user, rather than for their unique context.

We argue that organizations' implementation of AI technologies will perpetuate a new mechanism of isomorphism, through which the work practices of organizations will become increasingly similar over time, which we call *endogenous isomorphism.* Unlike mechanisms of isomorphism that depend on knowledgeable actors' responses to the externalities of the institutional field, *endogenous isomorphism* occurs as AI technologies implement patterns gleaned from aggregated data across time and space. As AI technologies learn from aggregated data gathered across organizations and make decisions based on what is likely to be helpful for the entire userbase, they implement practices that may intentionally or unintentionally lead to increased homogeneity in work (Hancock et al., 2020).

In this chapter, we discuss how artificial intelligence serves an endogenous mechanism of isomorphism in organizations. First, we discuss the nature of institutional isomorphism (DiMaggio & Powell, 1983) and how its mechanisms have been used to study the adoption of technologies. Second, we discuss why existing mechanisms of isomorphism are insufficient for studying how AI technologies shape organizations and how AI technologies' capabilities to learn from aggregated data and act autonomously lead to an endogenous mechanism of isomorphism when these technologies are embedded within organizations. Third, we offer possible outcomes of the endogenous isomorphism that artificially intelligent technologies make possible. Finally, we consider the implications of our arguments and discuss directions for future research.

Mechanisms of Institutional Isomorphism

Institutional isomorphism concerns the tendency for organizations' forms and practices to become more similar to one another over time. In their seminal work, DiMaggio and Powell (1983) define and describe institutional isomorphism as an explanation for how organizational homogeneity emerges. Drawing on Giddens (1979), DiMaggio and Powell argue that organizations resemble one another over time because of the structuration of organizational fields. In Giddens' (1979) language, organizations are structured by institutional-level structures such as professional standards, legislation, and norms. Organizations are enabled and constrained by these structures in their own structuring activities and also draw on these structures in order to produce action. Because organizations exist in shared institutional fields, their structuring efforts in response to institutional structures tend to resemble one another, such that organizational change does not lead to increased differentiation but increased similarity over time.

DiMaggio and Powell (1983) identified three mechanisms through which isomorphic change occurs in organizations. The first mechanism is coercive isomorphism, in which organizations become more similar to one another because of political influence and pressure to conform to cultural expectations. The second mechanism is mimetic isomorphism, in which organizations imitate one another as a means to manage uncertainty. The third mechanism, normative isomorphism, occurs when organizations' actions are shaped by growing professionalization, especially professional norms that are legitimized in communities of practice. These mechanisms have generated empirical work on organizations in areas such as entry (Koçak & Özcan, 2013), organizational strategy (Washington & Ventresca, 2004), corporate social responsibility (Lammers, 2003), and innovation (Tschang, 2007).

Each of the three mechanisms identified by DiMaggio and Powell (1983) assumes that institutional isomorphism occurs as organizations interact with and respond to actors in their surrounding social system, such as government agencies, other organizations, or professional communities. While the actions of these entities may shape the practices of a focal organization (i.e., creating sanctions, implementing new technologies, or adopting norms), they do so from outside the boundaries of the organization. We refer to these existing mechanisms of isomorphism as *exogenous isomorphism because* they are driven by organizations' responses to external entities.

Studies of technology and organizational change have drawn on institutional isomorphism to explain how organizations choose and implement the use of new technologies (Faik et al., 2020; Lai et al., 2006). For example, studies have shown how institutional isomorphism can lead organizations to adopt more sustainable technologies (Xu et al., 2022) and how organizations' dependence on information technologies mediates their likelihood of adopting them (Pal & Ojha, 2017). Other work has shown how companies strategically draw on discourse to shift institutional fields (Munir & Phillips, 2005), how organizational analysts attend to other organizations' decisions about technology implementation (Benner, 2010), and how professionals resist organizations' technological initiatives in the face of institutional isomorphism (Currie, 2012).

Existing studies of institutional isomorphism as it relates to technological change have primarily studied exogenous mechanisms of isomorphism. This work explains technological change largely as stemming from organizations' responses to their institutional field (Barley & Tolbert, 1997). Though studies have shown how the organization-specific changes in work practices that surround new technologies are enacted and negotiated among individual organizational members (Barley, 1986; Leonardi, 2009a; Prasad, 1993), when institutional isomorphism occurs, it is assumed to be exogenous in nature.

To study organizational decision making about artificial intelligence, exogenous mechanisms of isomorphism could be examined to understand how AI technologies are adopted and used within organizations. Such an approach could certainly make incremental contributions to our understanding of exogenous institutional isomorphism as it pertains to new technologies. Current research has shown, for example, that organizations are more likely to invest in artificial intelligence when they feel pressured to satisfy customers and to become more competitive within their institutional field (Iwuanyanwu, 2021). Caplan and boyd (2018) discuss the ways that organizations change their practices to adapt to other organizations' algorithms in their analysis of the Facebook newsfeed algorithms. And in one of the most extensive treatments of an institutional perspective on AI technologies, Larsen (2021) distinguishes institutional and digital realms to argue that both institutions and digital infrastructure shape how organizations manage the uncertainty of adopting AI technologies.

Each of the studies described above contributes to our understanding of how mechanisms of exogenous isomorphism shape organizations' decisions about implementing AI technologies. In these studies, however, AI technologies are treated in the same way as any other type of technology . AI technologies are also treated as the outcome of isomorphism, i.e., if and how AI technologies are adopted and the practices through which people bring them into use (Orlikowski, 2000) are the outcomes of organizations' response to external forces.

However, such an approach is limited because AI technologies are not like all technologies. Unlike other iterations of digital technologies, AI technologies are capable of learning and of making decisions without explicit human instruction. In the next section, we describe the capabilities of AI technologies to act autonomously and learn. In combination, these capabilities allow AI technologies to shape organizational actions such that they are more similar to other organizations from *inside* the boundaries of the organization, a mechanism thar we call *endogenous isomorphism.* Relatedly, AI technologies are then not only the outcome of isomorphism but also actors that make isomorphism possible. We discuss why these capabilities require theorizing the use of AI technologies as the *engine* of organizational change towards homgeniety, not only as the *outcome* of organizations' isomorphic decision making.

Artificial Intelligence and Endogenous Isomorphism

Artificial intelligence, most broadly, refers to computational processes designed to mimic human intelligence (Nilson, 2010). Generally, artificial intelligence refers to complex predictive models that can outperform human decision making as opposed to rule-based computations (Berente et al., 2021). Technologies equipped with artificial intelligence have two capabilities that are relevant to their capacity to shape organizational practice. The first capability is that AI technologies can learn, improving their decision making through computational processes without explicit human instruction. The second capability is that AI technologies are capable of making decisions autonomously on behalf of people and organizations, as opposed to only facilitating human decision making. Below, we describe how these capabilities work together to make AI technologies' decision making a mechanism of endogenous isomorphism.

Like human intelligence, artificial intelligence relies on processes of learning to improve over time. Machine learning, or the processes through which AI technologies improve, occurs as AI technologies encounter data. AI technologies begin their learning by analyzing training data, a labeled set of data from which AI technologies can identify patterns between actions and particular outcomes that are either inductively identified or specified by a programmer (Nilson, 2010). AI technologies may not work effectively at first because they are still learning to account for a range of possible use cases (Shestakofsky & Kelkar, 2020), but over time, AI technologies are designed to learn from users. As actors naturalistically use AI technologies in a range of social settings, they generate a wider, more robust set of data that then facilitates machine learning. While digital technologies without artificial intelligence are improved through human action (i.e., changing written code, fixing glitches, Neff & Stark, 2004), AI technologies can learn and refine their predictions from data themselves.

In addition to being able to learn from data, AI technologies are also capable of making decisions without explicit human instruction. While many AI technologies are designed to respond to human prompts (i.e., natural language requests such as prompts for AI-generated imagery or voice commands to virtual assistants), they can respond to these prompts without explicit instruction about how to do so. AI technologies vary in the extent to which they autonomously execute their decisions (for example, some AI technologies offer suggestions to users whereas others take action without any human input, see Endacott & Leonardi, 2022), but share an ability to make decisions without being given exact parameters. Increasingly, AI technologies make these decisions on behalf of actors – for example, making decisions to direct customers toward different services on behalf of organizations or making decisions about work pratices on behalf of individuals in organizations. AI technologies' capability to make decisions on behalf of others allows them to meaningful shape organizational practice through the actions that they generate and implement.

Taken together, AI technologies' capabilities to learn and autonomously make decisions form two logics that shape their actions: aggregation and optimization. By logics, we mean the "organizing principles" through which AI technologies operate (Thornton & Ocasio, 1999, p. 804) and the guiding values through which the work of these technologies is conducted (Anteby et al., 2016; Thornton et al., 2012). *Aggregation* refers to sophisticated AI technologies' reliance on wide swaths of data to identify patterns that are robust across use cases. *Optimization* refers to AI technologies' aim to predict which decisions have the highest probability of securing desired outcomes. As AI technologies' work is guided by the logics of aggregation and optimization, these technologies make decisions based on what is most useful to a wide userbase, inclusive of a variety of social contexts. In other words, AI technologies make decisions that are suitable for a given set of constraints for the average user.

The challenge that the logics of aggregation and optimization pose to organizational practice is that most organizational decision making does not occur with the premise that choices should be appropriate across social settings. Most organizational decision making occurs based on what is appropriate for the specific social context of the organization, given its surrounding institutional field. Because different fields have different institutional logics, organizations vary in the "assumptions and values, usually implicit" through which organizational reality should be interpreted and behavioral decisions made (Thornton & Ocasio, 1999, p. 804). While the premise of institutional isomorphism assumes that organizations are affected by other organizations that share their normative expectations, it does not assume that organizations are affected by all organizations. Instead, organizations make decisions that are mechanisms of isomorphism based on the actions of other *relevant* organizations. For example, DiMaggio and Powell propose that organizations are more likely to model organizations on which they are dependent. Such a view assumes that organizational practices are selected based on the likelihood that they are the right courses of action for a particular time, place, and social group.

If AI technologies make decisions based on what is best for the entire userbase and organizations make decisions based on what is best for their specific organization, then organizations' decisions to implement AI technologies contrive an occasion in which organizational practices shift. As AI technologies make decisions based on aggregation and optimization, they implicitly select practices that combine a set of potentially conflicting institutional logics. The situated nature of organizational decision making is transformed into a process shaped by what is best for the average actor (i.e., individual user or organization).

The selection of practices by AI technologies that are learning from aggregated data presents the possibility of practices becoming stretched over time and space into realms in which they did not originate, a phenomenon that Giddens (1984) called *time-space distanciation*. As AI technologies implement work practices that are probabilistically best for the average user, they replace practices that are specific to the organizational field, replacing domain-specific actions with homogenized ones. For example, Hancock et al. (2020) describe how written text can become homogenized when it is drafted using AI suggestions using the example of Google's predictive text function. As users draft emails, the function automatically suggests text based on data gathered from all users' emails. For example, if a user begins to write, "I hope," suggested text of "this finds you well" will be displayed. It could be, however, that the user had intended to write "I hope you're staying safe." But the machine learning algorithms that power this tool must predict text based on what is most likely to be optimal for the greatest number of users. If more and more users accept the suggestions of the tool, a likely outcome is that writing in general will become more homogenized, as people implement the patterned work practices gleaned from big data analysis that are suggested or implemented by AI technologies.

To the extent that these AI technologies can autonomously choose organizational practices, organizations may be made more similar to one another over time. AI technologies are capable of making decisions about organizational practices such as hiring (van den Broek et al., 2021), meeting with coworkers (Endacott & Leonardi, 2022), communicating with customers (Pachidi et al., 2020), and allocating organizational resources, i.e., deploying staff (Waardenburg et al., 2022). In outsourcing any one of these organizational practices to AI, organizations may find that practices are transformed to be more like the average use case. Some technologies may draw on more field-specific data to make decisions (for example, predictive policing would learn from data gathered across cities related to policing) but other technologies draw on data from a variety of institutional fields (for example, scheduling tools learn from a variety of organizations involved in knowledge work). In both cases, however, AI technologies enact mechanisms of isomorphism because the logics through which they make decisions requires identifying practices likely to hold across institutional fields or across organizations within an institutional field.

Because of the opacity of machine learning processes, many organizations may not even realize the criteria through which AI technologies are making decisions nor the scope of the data on which they are trained. Burrell (2016) describes this type of opacity as emerging from the scale of data on which machine learning algorithms are trained. Because so many data points with “heterogenous properties” are analyzed in machine learning, the criteria on which decisions are made becomes increasingly complex (Burrell, 2016, p. 5). No singular organization will be able to sufficiently understand the scope and nature of the data from which a particular AI technology is learning nor would it be able to offer the same complexity of predictions. This opacity allows AI technologies to implement organizational practices gleaned from aggregated data without organizations' explicit awareness that they are doing so. This dynamic, in which AI technologies can choose organizational practices that regress toward the mean from inside the boundaries of the organization, led us to call this a mechanism of endogenous isomorphism.

To this point, we have discussed how AI technologies can bring about endogenous isomorphism largely in the abstract. Next, we offer one illustrative example of how endogenous isomorphism occurs from our ongoing study of AI scheduling technologies (see Endacott & Leonardi, 2022).

An Illustrative Example of Endogenous Isomorphism: Artificially Intelligent Scheduling Technologies

We researched how artificial intelligence was being used in the domain of scheduling. We studied a company, which we call Time Wizards, that was striving to develop a conversational agent that could schedule meetings on users' behalf. The conversational agent, which could be given the feminine name "Liz" or the masculine name "Leo," could be used by individual users with others within their organization or with people outside of it to schedule meetings in natural language. In adopting this AI technology, users ceded control over their calendar and how decisions about their schedule were communicated to others by Liz or Leo.

We spoke to five developers at the company about the processes through which Liz and Leo were designed to learn. The developers affirmed that users wanted Liz and Leo to learn from within-case data, or to learn from their patterns alone. For example, one developer, Diego, the lead data scientist for the company, explained that if the tool could "pre-populate preferences for the user based on their calendar, like based on their habits, that would delight them."

Despite user interest in a tool that would learn their unique patterns, it was clear from interviews with developers that the tool was designed to learn from all aggregated data. Developers described how their tool was designed with a logic of aggregation. For example, co-founder Mikkel explained how the value of their tool lay in the vast degree of data from which it would learn. He explained, "On an individual basis, you can't really do any optimization in your own inbox. It's too sparse of a dataset, you don't have the time, you don't really think about it. But we [as an AI company] can start to really think about this." Diego explained that the tool needs to learn from many, many data points so it can accurately guess at what a user wants and what it should do next. He said,

> "You need to collect data for both. You need to figure out what it needs to be right or wrong, in both of these cases. The understanding part makes it easier, 'cause then you're not, like just scheduling meetings on your own. What I can say is after looking at a million meetings, I can say at this juncture of the meeting, people typically want to say one of these twenty things."

These quotes indicate that the complexity of decisions made by the AI agent required learning from aggregated data collected across the userbase, suggesting that our proposed logic of *aggregation* shapes the work of this AI technology.

The aggregated data from which Liz and Leo learned allowed the tool to make decisions using the logic of optimization. As Diego explained, "Liz is trained in aggregate and the dialogue is optimized in aggregate." Diego's comments suggest that Liz and Leo could generate appropriate responses in natural language because they have learned from aggregated data.

Mikkel explained that Liz and Leo then learn how to make decisions about work practices and how optimal actions begin to emerge from the data. He explained how Liz and Leo learn how to optimally negotiate the time and duration of meetings:

> "You [the developer] can certainly chart it in such a way that you can start to see which particular paths, dialogue paths, are more likely to yield success because if I can see that this certain path that is more likely to yield success then I can start to direct the dialogue, like any good negotiator, down a path where I am now more confident that you and me will come to a positive outcome."

Mikkel and Diego's comments suggest that the logic of optimization did shape how their AI technology was designed to make decisions about the practices that should be implemented on users' behalf.

To learn how AI technologies shaped organizational practices, we also interviewed users of Time Wizards' technology. We spoke with fifteen users about their use of Time Wizards' AI agent. We contacted users again six to nine months after their first interview to ask them to participate in a second interview so that we could better understand how their use of the technology shaped work. 13 of the original 15 users participated in a second interview. Some users worked in larger organizations (i.e., as technology officers, researchers, or sales professionals) while most worked in small businesses (i.e., small consulting firms, start-ups, financial advising office). Some users worked with organizations as contractors, i.e., business consultants.

Users described how once they started using Liz and Leo, they noticed that the tool scheduled them differently than they would do themselves. Often, users described how the tool scheduled them in ways that would be appropriate for someone in sales or recruiting, who had a high volume of meetings that were relatively similar in time and duration. For example, users Joe and Bob both described the perfect user for the tool as "a recruiter or kind of a salesperson" (Joe). Joe, who ran a small consulting company for the legal field, explained that the tool is designed to help someone with a high "volume and uniformity" of meetings. Some users noticed that their meeting needs were quite varied. As Bob, a business consultant, explained,

> "I'm very rarely giving somebody an audience. Not because I'm a jerk, just that my role doesn't call for it right now. Recruiters and salespeople, meetings where someone's doing me a favor – I don't do a lot of that anymore. It's more often, I'm putting together strategic partnerships where it's me and a couple of other people at my level trying to figure out how to make something happen."

Another user, Richard, described that based on how the tool made decisions, the perfect user would be "a salesperson or a dev[elopement] type person whose primary thing is they want to set up meetings." These quotes show that users understood the tool as designed to optimize the number of meetings in which they participated in a given week.

As users outsourced their scheduling practices to the AI agent, they noticed that their schedules became more similar to that of a recruiter or salesperson. For example, Bradley, who worked for a startup, explained that his work had typically involved some meetings but also more independent creative work. Since using Leo, he explained that he has "more external meetings, more meetings with new people." Many users shared Bradley's observation that they had many more meetings since using Liz and Leo. For example, Nathan, an organizational consultant, noted that "Liz would grab a slot when really it wasn't going to be convenient, because I was sort of between appointments." Joe explained that the tool's "default" is to schedule "ASAP, so if you have 3pm available this afternoon and so does this guy, the meeting will be scheduled then." The tool's prioritization of scheduling meetings as quickly and as often as possible led one user, Jenn, to facetiously speculate that the start-up company that made Liz and Leo forgot to add a feature that allows time for lunch because "in the startup world, everyone works 20 hours a day, drinks Soylents and eats power bars to keep going and don't necessarily think about how other people might want bathroom breaks or time to eat lunch."

Without active intervention, Liz and Leo arranged users' work based on what the tool was trained to do: negotiate meetings as efficiently as possible, as optimized for the greatest amount of successfully scheduled meetings. For users whose work deviated from the norms of a salesperson or recruiter, they experienced an influx of meetings onto their calendar. Their work began to resemble that of a salesperson, who made up a significant portion of Time Wizards' userbase. One user, Benjamin, who oversaw company partnerships for the government, pointed out that this transformation of work had taken a toll on him, even though meetings were vital to his work. He said, "The robot doesn't know that I'm hungry and need a break… I get tired of the sound of my own voice." He said that he had meetings scheduled with people who, if he had to schedule the meetings himself, he would not have chosen to meet. Using Liz and Leo has changed his "understanding of getting work done and how much there is to do and how if I don't [schedule my work blocks], my schedule will be full, and then I won't get any of that time for my work." As Benjamin's comment shows, users perceived that the practices through which their work was organized and accomplished were changed as they entrusted an AI agent to manage their calendars. The practices were arranged according to the logics by which the AI agent was designed to act, as enabled by the aggregated data from users across many different work contexts.

Potential Outcomes of Endogenous Isomorphism

AI technologies' endogenous shaping of organizational practices to be more similar to the average case yields several potential significant outcomes for organizations. Certainly, as recent studies have shown, the implementation of patterns located in training data can perpetuate bias, for example, in client services in policing (Brayne & Christin, 2020) and medicine (Lebovitz et al., 2022). But a more subtle effect of the homogenization of work may also be a reduction in the requisite variety of inputs, including knowledge and practices, needed to facilitate organizational creativity and innovation (Weick, 1979). Organizations should consider if, when, and how they should retain variation as work processes are increasingly mediated and organized by artificial intelligence. Below, we describe how the mechanism of endogenous isomorphism could lead to a spread and reinforcement of work-related bias and lower requisite variety for innovation, but also a greater awareness of organizational practices.

Spread and Reinforcement of Work-Related Bias. One potential outcome of endogenous isomorphism is the spread and reinforcement of work-related bias. Ongoing conversations about the ethics of artificial intelligence have focused on the ways that bias related to gender, race, and class can become perpetuated by AI technologies that learn from biased data (i.e., Brayne & Christin, 2020; Cirillio et al., 2020; Lebovitz et al., 2022; Rudin et al., 2020) But AI technologies can also be biased toward particular logics of work. This bias can arise through aggregation. If enough of userbase works or makes decisions in a similar way, the AI technology will learn to imitate those patterns (i.e., the 'recruiter' or 'salesperson' in our example above). The bias can also stem from optimization, as the outcome criteria for which the tool is trained to pursue can reflect bias about the ideal mode of working or organizing (i.e., Time Wizards' developers optimizing their agent to make as many meetings happen as possible). As AI technologies stretch practices across time and space, they may reinforce the dominant logics through which work is organized.

Lower Requisite Variety for Innovation. Across theoretical perspectives, including evolutionary models of organizational routines (Weick, 1979), behavioral theories of the firm (March, 1991; Simon, 1997), and network theories of innovation (Leonardi & Bailey, 2017; Uzzi & Spiro, 2005), a shared assumption is that organizations need to experience a certain degree of variety in their organizational practices in order to learn and innovate. If organizations increasingly use AI technologies to make decisions about their work, it is likely that there will be lower variety of practices both within organizations and across organizations. Within organizations, AI technologies may implement decisions that are less reactive to specific situational contexts, because the technologies are optimized for fixed outcomes. Across organizations, increasing use of AI technologies may reduce the variety of organizational practices because these practices serve the needs of the crowd, rather than the preferences of the individual user. Such homogenization may ensure that the most data-supported best practices (as determined by the userbase) are implemented in organizations, but it may also reduce the requisite variety of actions that organizations can select and retain (Weick, 1979).

More Awareness of Organizational Practices. One potential unintended but useful consequence of organizations deploying AI technologies is that doing so may help organizations interrogate their practices. As our illustrative example of AI scheduling shows, users became more aware of how their own work was organized when they implemented an AI agent to schedule on their behalf. They noticed ways that the tool shaped their work to pursue different logics than they themselves used when organizing their workday. As AI technologies introduce new organizational practices into an organization's landscape, it may serve as an occasion for organizations to better understand taken-for-granted structures. When organizations are better positioned to understand and articulate their practices, they may be more apt to interrogate them and change them if necessary.

Implications

In this chapter, we have theorized the implementation of AI technologies that can make decisions about organizational practices on behalf of organizations and individuals as a mechanism of endogenous isomorphism. Rather than exerting organizational change towards homogeneity by eliciting a conscious organizational response to outside pressures, we argue AI technologies push organizations toward homogeneity by implementing organizational practices that are selected via aggregation and optimization. Because the sources of data and the process through which decisions are selected are often opaque, AI technologies can implement change without organizational knowledge from within the boundaries of organizations themselves. Below, we discuss the implications of this argument for theories of technology and, institutional isomorphism, the methodological implications for studying intelligent technologies, and practical implications for organizational leaders.

Theoretically, our chapter offers a new way for technologies to be implicated in isomorphic change: as implementors of new organizational practices, rather than as the content of that change. Our argument moves beyond technological adoption as an outcome of isomorphism to theorize how intelligent technologies that can make decisions on behalf of organizations introduce new practices into an organizational setting. Such an approach highlights how existing theoretical perspectives like institutional isomorphism can be reconfigured to account for the unique characteristics of AI (the ability to learn from aggregated data and to probabilistically make decisions based on that learning). Theorizing AI technologies as actors within institutional fields has the potential to yield a much more significant intellectual contribution than continuing to examine how organizations make decisions about whether to adopt AI.

Practically, understanding the implementation and use of AI technologies as a mechanism of endogenous isomorphism may help organizations be more attuned to intended and unintended consequences of novel technologies. Without greater awareness, organizational leadership may assume that AI technologies are designed to learn from their specific organizations, which may make them less likely to question decisions made by AI. By highlighting the logics through which AI technologies make decisions, our argument may help organizations become more aware of ways in which AI technologies make decisions that depart from their desired institutional logics. In such instances, human input might be especially useful in overriding or amending decisions made by AI (Kang & Lou, 2022; Schestakofsky & Kelkar, 2020). When organizations are mindful of AI technologies' capacity to transform their practices, AI technologies may contrive occasions for organizations to notice areas in which practices diverge from existing routines, allowing them to retain and enact the most useful changes.

The conceptual argument presented here also has methodological implications. Future research on AI technologies will require deep understanding of processes on both sides of the implementation line, i.e., of both development, including machine learning, the outcomes for which algorithms are optimized, and the nature of training data, and of use, including changes that AI technologies may bring about in situated organizational contexts (Bailey & Barley, 2020; Leonardi, 2009b). One analytical strategy could be to design studies to elicit the underlying institutional logics of both the AI technologies and the organizational contexts into which they are embedded. A researcher could select several cases to see if, how, and when an organization's existing institutional logics are reconfigured by implementation of AI technologies. That research design might help illuminate use cases in which organizations would be especially susceptible to endogenous isomorphism.

Our argument is not without its limitations. One possible critique of our discussion here is that our endogenous mechanism of isomorphism may be capturing the diffusion of forms and practices (i.e., “mere spread”, Greenwood & Meyer, 2008, p. 262). rather than on the true institutionalized practices that DiMaggio and Powell first described. We believe future research can assess the extent to which AI technologies change organizational practices to adhere to different institutional logics by studying AI technologies as they are implemented and used in organizations. Qualitative field research may be especially helpful in surfacing the institutional dynamics involved in AI implementation.

Conclusion

In this chapter, we theorized a new mechanism of isomorphism that is brought about AI technologies that operate through logics of aggregation and optimization: endogenous isomorphism. Understanding how AI technologies transform organizational practices toward greater homogeneity is important to understanding how organizations will adapt and change within an increasingly AI-mediated institutional landscape.

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