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POINT OF VIEW

# Moving beyond human-centric organizational designs

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**Abstract**

Investments in artificial intelligence, autonomous robotics, and similar technical systems continue to accelerate as organizations pursue opportunities to strengthen their performance and create even greater value for stakeholders. Despite voluminous guidance and best practices on designing and operationalizing such technical systems, many organizations are not achieving their expected returns and performance levels. The problem might be a biased view of organizations as primarily human-centric systems, which can place unnecessary limits on the performance of intelligent robots, artificial intelligence, and similar technical systems. Reimagining and purposefully designing organizations as systems composed of human and non-human knowledge workers co-performing tasks for organizational goal attainment can generate more robust performance and strengthen corporate returns on investments in such sophisticated systems. Non-human knowledge workers (NHKWs) are synthetic computational agents characterized by the conjunction of four attributes—information processing power, knowledge work, task-level employment, and more comprehensive organizational integration—distinguishing them from more common artificial intelligence, autonomous robotics systems, and autonomous vehicles frameworks. More gainful employment of NHKWs, and similar systems, is primarily a design issue and one that is largely separate from the capabilities NHKWs might possess. Using an organizational technology framework, this paper offers managers and organizational designers a systematic approach that can harness NHKW capabilities more effectively, thereby producing stronger organizational performance.

**Keywords** Artificial intelligence · Computational agents · Robots · AI boss · Algorithmic manager · Cognitive bias · Team performance · Organizational design

**JEL Classification** D23 · L2 · L22 · L23 · L25

## Introduction

In the pursuit of their goals, organizations are increasingly investing in artificial intelligence, autonomous robotics, autonomous vehicles, and similarly advanced technical systems. Such artificial intelligent systems (AIS) can possess remarkable capabilities that oftentimes exceed those of humans.[1] Moreover, AIS are not necessarily limited cognitively, physically, and temporally as humans are (Carley and Gasser 1999; Kahneman 2013; Perrow 1999). Despite significant investments in and guidance on deploying artificial intelligence, such as MIT's Machine Intelligence for Manufacturing & Operations (https://mimo.mit.edu), many organizations do not appear to achieve their expected results (D'Silva and Lawler 2022; Datta 2020; Fountaine et al. 2019; Mittal et al. 2022). Compounding the problem, more companies are investing in AIS, as they become increasingly available and affordable, resulting in a growth in the relative number of companies underachieving their performance expectations (Mittal et al. 2022). Recommendations abound regarding how organizations can obtain stronger results from AIS; they generally emphasize better messaging by executives, C-suite commitment, selection of pilot projects,

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[1] Humans gather, process, and exchange information for a variety of purposes (Schroder et al. 1967), which makes humans, themselves, information systems. The term *AIS* is used to distinguish artificial systems, such as intelligent robots (Burton et al. 2021, 2023) and intelligent autonomous systems (Burton et al. 2020; Kuru and Khan 2021), that similarly gather, process, and exchange information from humans and other natural information systems. The benefits of using the term AIS to assist distinguishing between natural and artificial systems, and for concision seem to outweigh potential issues resulting from its use elsewhere.

governance, selection of development teams, and employee training (D'Silva and Lawler 2022; Datta 2020; Fountaine et al. 2019; Mittal et al. 2022; Saran 2022).

A prevalent view of organizations as primarily human-centric systems, however, might be the problem—a bias that can have two important effects on task and organizational designs, negatively impacting performance. Importantly, this perspective and the associated effects are design issues—not necessarily AIS capability issues. First, this perspective means that humans wield technical systems, including AIS, to perform tasks (Burton et al. 2021; Mintzberg 1993; Perrow 1967, 1999): this relationship, in turn, results in imposing limitations associated with human performance onto technical systems (Kahneman 2013; Rabb et al. 2019; Sloman & Fernbach 2017). Second, this perspective can result in task designs that do not take full advantage of AIS capabilities (Burton et al. 2021; Puranam 2021; Puranam and Mehra 2022). These effects, individually and combined, can limit the extent to which AIS contribute to organizational performance and stakeholder value generation, including returns on investments in AIS. As Frick (2015) remarked, "As these machines evolve from tools to teammates, one thing is clear: Accepting them will be more than a matter of simply adopting new [technical systems]." This raises the question—*does a human-centric systems view of organizations unnecessarily limit their performance and goal attainment?*

Stronger organizational performance and stakeholder value generation likely mean moving past a long-standing and biased view of organizations as human-centric systems. Organizations designed to employ non-human knowledge workers (NHKWs) alongside human knowledge workers (HKWs) in the technical core are likely to outperform organizations that treat AIS as solely technical systems (D'Silva and Lawler 2022; Datta 2020; Fountaine et al. 2019; Mittal et al. 2022). However, managers and organizational designers probably possess a bias—one that appears to hold many organizations back from attaining their goals. This paper highlights this perspective, describes it as primarily a design issue, and proposes a different framework that employs NHKWs alongside HKWs. The coexistence of NHKWs and HKWs as technical core members recharacterizes the perceived relationship between HKWs and AIS and entails engineering tasks to take greater advantage of NHKW capabilities. This framework allows NHKWs to impact organizational performance and stakeholder value generation more significantly, thereby enabling organizations to generate greater performance and stakeholder value than they can, otherwise. The discussion begins with describing the assumed relationship between HKWs and AIS and the associated impacts on task performance, using the context of organizational technologies. Then, the perspectives of major schools of organization theory and how they have shaped the human-centric view of organizations are summarized. Next, the construct of NHKWs is explored, using examples from food delivery and rideshare companies. Lastly, an example of a NHKW boss employed by a rideshare company is provided.

## The human nature of organizations

Managers and designers of modern organizations are likely ill-served by the prevalent view of organizations as human-centric systems, which has existed for well over 100 years. Addressing the effects of this view on organizational performance necessitates understanding the scholarly traditions in which it is grounded. This section summarizes the perspectives of major schools of organization theory that have shaped how practitioners and scholars comprehend organizations, particularly their perceived human-centric nature. An organizational technology provides a relevant framework for both understanding the effects that this common view has on organizational performance and what managers and organizational designers might need to do to overcome those impacts (Mintzberg 1993; Perrow 1967; Snow et al. 2017).

The view of organizations as mainly human-centric systems is foundational to the classical, neo-classical (a.k.a., human relations), and modern schools of organization theory. This perspective results in designing organizations as systems in which people apply their knowledge and skills using hand tools, machines, software algorithms, and other technical systems according to relevant processes and practices to perform tasks (Arrow 1974; Burton and Obel 2004; Mintzberg 1993; Perrow 1967, 1973).[2] Inherent to this model is an assumed relationship between humans and technical systems—that humans wield technical systems—thereby imposing limitations associated with human performance onto technical systems, themselves (Arrow 1974; Kahneman 2013; Puranam 2021). The net result is this biased view of organizations—in which AIS are simply treated as tools—effectively limits the nature and scope of AIS contributions to group performance and goal attainment.

An organizational technology model provides a system-level framework for discussing the relationship between humans and technical systems, as assumed by humans—and what the relationship could be. Simply, an organizational technology describes how teams, groups, and firms transform raw system-level inputs into outputs and operationalize an organization's strategy (Snow et al. 2017). An organizational technology comprises its technical core, technê, tasks, techniques, and technical systems (Mintzberg 1993;

[2] The terms *human*, *person*, *individual*, and their plural forms are used interchangeably, for the most part, in this paper.

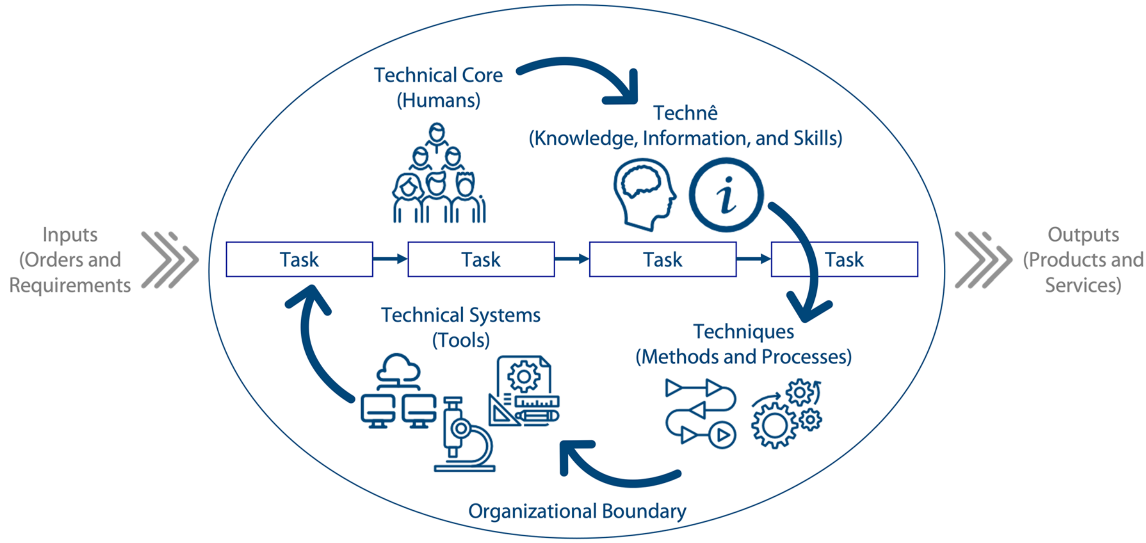


**Fig. 1** Illustration of an organizational technology model. Organizational goal attainment necessitates the transformation of system inputs, such as product orders and service requirements, into outputs, such as products and services. Within organizational boundaries, members of the technical core apply their technê according to relevant techniques and use technical systems to perform tasks that reify the organization's strategy. Adapted from Jansen (2000)

Mortimore et al. 2023a, 2023b; Perrow 1967). The *technical core* is made up of individuals involved in converting system inputs into outputs (Mintzberg 1993; Perrow 1967). *Technê* refers to the task and cognitive specializations (i.e., expertise) and skills possessed by technical core members and the organization, as a whole, to perform *tasks*, which are groupings of activities purposely performed on inputs in the technological transformation process (Drucker 1988, 1993; Lawrence and Lorsch 1967; Thomas and Velthouse 1990). *Techniques* refer to the set of methods performed via processes on system inputs (Perrow 1967) and provide technical core members approaches for applying their expertise. *Technical systems* are the physical and non-physical tools that technical core members use to perform activities and tasks (Perrow 1967; Thompson 1967). In other words, an organizational technology is *how* an organization accomplishes its mission. Figure 1 depicts a generic organizational technology.

The classical school of organization theory effectively posits humans as the users of technical systems, in spite of the school's mechanistic approach to organizations. Although the classical school treats humans as little more than cogs in organizational apparatuses (Perrow 1973), laborers and managers are clearly the wielders of tools (Gulick 1937; Taylor 1911; Weber 1964). The relatively unsophisticated nature of technical systems in the 1800s and first half of the 1900s likely helped to shape the perceived relationship between humans and technical systems. Moreover, the division of labor—for which scholars and practitioners advocated—set and reinforced the assumed organizational relationship between humans and technical systems (Fayol 1916; Gulick 1937; Smith 1776; Weber 1964). By stressing formalized authority and rules, standardization of tasks, and hierarchical authority structures (Fayol 1916; Gulick 1937; Taylor 1911; Weber 1964), the classical school entrenched a bias regarding the human nature of organizations—a bias that remains largely intact today and appears to hold organizations back from realizing greater performance. Figure 2 illustrates, in the context of the classical school of organization theory, the typical relationship of technical core members and technical systems—one that reflects humans as users of AIS.

In contrast, the neo-classical school places individuals and social networks in the forefront of organizations, thereby reinforcing the predominant view of organizations. People, not machines and processes, drive organizations and their performance: technical systems exist to facilitate cooperative task performance (Barnard 1938; Cyert and March 1963; Selznick 1948). By further legitimizing the view of organizations as human-centric systems, the neo-classical school effectively dissuades scholars and practitioners from scrutinizing the make-up of the technical core as a design parameter—the primarily human nature of the technical core is taken almost as a matter of faith. Divisions of labor and the associated specializations developed and reinforced by such divisions continue as mainstays of organizational design: developing and employing specialized knowledge and skills positively impact organizational performance and the standing of individuals (Barnard 1938; Mayo 1945; Simon 1947). Applying expertise and skills in the pursuit of organizational

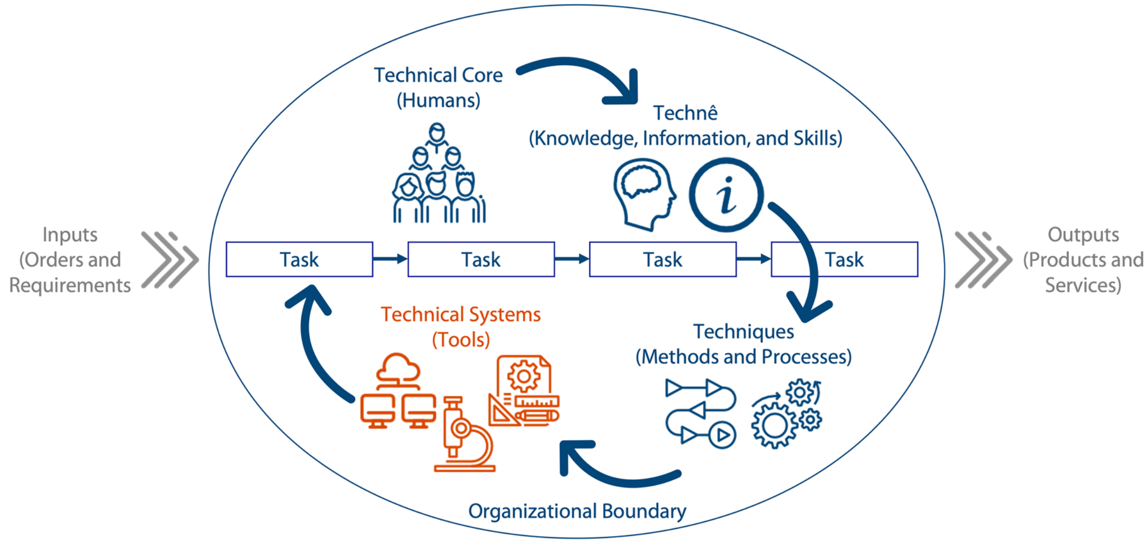


**Fig. 2** Classical school organizational technology model. Notwithstanding its mechanistic view of organizations, the classical school of organization theory treats humans as the users of technical systems (highlighted in orange), thereby establishing a design relationship between them that effectively ties organizational performance to human performance. Adapted from Jansen (2000)

goals necessitates people use technical systems to perform tasks. Consequently, cognitive, physical, temporal, institutional, and other limitations associated with human performance continue to condition organizational performance (Carley and Gasser 1999; Kahneman 2013; Narayanan et al. 2022; Perrow 1999). Accordingly, the general organizational technology model for the neo-classical and classical schools is largely the same (see Fig. 2): people perform tasks using physical and non-physical technical systems.

The modern school of organization theory further affirms the biased view of organizations as primarily human-centric systems and perceived relationship between humans and technical systems. Notwithstanding the representation of organizations as information processing and communication systems (Arrow 1974, 1996; Galbraith 1977; March and Simon 1958), the modern school emphasizes people (Cohen and March 1974; Cyert and March 1963; Galbraith 1977), divisions of labor (Galbraith 1977; Nadler and Tushman 1988; Thompson 1967), the development and employment of distributed expertise and skills (Simon 1973; Malone and Crowston 1991; Wegner et al. 1985, 1991), and the human use of technical systems (Arrow 1974, 1996; Daft and Lengel 1986; Puranam 2021). Against the backdrop of modern and rapidly advancing technical system capabilities, organizations continue to be thought of, designed, and managed as human-centric systems—with AIS perceived mainly as work aids (Burton et al. 2023; Davenport 2016; De Cremer and McGuire 2022; Haesevoets et al. 2021; Xu et al. 2022). Unsurprisingly, the general organizational technology model for the modern school remains largely unchanged from the classical and neo-classical schools (see Fig. 2): the result is that organizational performance and stakeholder value generation remain limited by human performance (Arrow 1974; Puranam 2021; Simon 1973).

Relatively recent publications and the broader body of literature, while robust, largely miss the mark because they inadequately address the nature of organizations as complex systems. In highlighting the impacts that AIS can have on organizational performance, recent studies do not explicitly address the constitution of the technical core, itself (Burton et al. 2019, 2021, 2023; Davenport et al. 2020; Fountaine et al. 2019; Huang et al. 2019). While some studies advocate treating AIS as a teammate, in the context of a sociotechnical system (Cummings and Markus 1979; Makarius et al. 2020), that alone is inadequate to generate the organizational results envisioned (Frick 2015; Buettner 2007; Snow et al. 2017). Instead, contemporary studies generally investigate: the acceptance and trust of AIS in sociotechnical systems (Cao et al. 2021; Glikson and Wooley 2020; Haesevoets et al. 2021; Mahmud et al. 2022); the sequencing of work and use of specialized and non-specialized technê (Christiansen and Knudsen 2013; Endsley 2017; Jain et al. 2022; Puranam and Mehra 2022); and human–machine team membership (Grønsund and Aanestad 2020; Makarius et al. 2020; Parry et al. 2016; Puranam 2021). Similarly, studies that address the divisions of labor (Agarwal et al. 2018; Dellermann et al. 2019; Makarius et al. 2020; van Dongen and van Maanen 2013) and purposeful use of specialized knowledge and skills (Jarrahi 2018; Murray et al. 2021; Seeber et al. 2020; Tinguely et al. 2023) in organizations in which people and AIS coexist generally leave undisturbed the fundamental perceptions regarding the human nature of organizations and associated relationship between humans and technical systems. Therefore, it is no surprise that calls for additional exploration of designs for HKW and NHKW ecosystems exist (Parker and Grote 2022; National Academies of Sciences, Engineering, and Medicine (NASEM) 2019; Puranam 2021).

In the context of organization theory, people wield tools; tools generally do not perform tasks apart from their wielder. The perception that the technical core is primarily human in nature is common to major schools of organization theory and the broad acceptance of this view seems to have resulted in it becoming an unchallenged assumption when designing and managing organizations. This widely held view results in organizational technologies wherein human technical core members apply their technê and skills by using AIS, as forms of technical systems, according to relevant methods and processes. This relationship between people and tools results in the imposition of cognitive, physical, temporal, and other limitations associated with human performance onto AIS (Carley and Gasser 1999; Kahneman 2013; Perrow 1999). Imposing such limitations onto AIS is particularly problematic when AIS capabilities approximate and, in some cases, exceed human capabilities. Therefore, designing and managing organizations as human-centric systems unnecessarily limits organizational performance and goal attainment—as firms and other organizations are experiencing (D'Silva and Lawler 2022; Datta 2020; Fountaine et al. 2019; Mittal et al. 2022; NASEM 2019).

## Moving beyond human-centric designs

The purposeful employment of NHKWs as technical core members affords organizations an opportunity to move past performance limitations associated with human-centric designs. NHKWs are synthetic computational agents that conjoin four attributes: information processing power that is at least commensurate with HKWs; performance of mostly knowledge work; task-level assignments; and more systematic incorporation into organizational structures (Mortimore et al. 2023a, 2023b). Together, these attributes effectively re-characterize the nature of an organization as an HKW–NHKW ecosystem: one in which NHKW contributions to organizational performance and stakeholder value generation are less limited by human performance and associated task designs.

First, NHKWs possess information processing power, algorithmic and otherwise, commensurate with or superior to HKWs. Like their human counterparts, NHKWs can possess a range of information processing capabilities and frameworks, both internally and externally constructed (Schroder et al. 1967): it is only necessary for NHKWs to process information commensurate with some HKWs, such as more junior personnel, not all human technical core members. The information processing power of synthetic computational agents, which are forms of AIS, used by Deliveroo, Uber Eats, Lyft, and Uber generally exceeds the capabilities of a HKW performing similar tasks (Lee et al. 2015; O'Connor 2016; Rosenblat 2018).[3] The AIS continuously gather, process, and act upon a greater volume of organizational system inputs, such as food delivery orders, than a HKW can likely do (Lee et al. 2015; Rosenblat 2018). The AIS can also process greater volumes of information stemming from, and more rapidly respond to, uncertainty inherent in the organizational technologies of the four firms (Lee et al. 2015; O'Connor 2016; Rosenblat and Stark 2016). The non-standard constitution of technical cores, in terms of the number, location, order acceptance, and performance of delivery personnel and rideshare drivers, varying levels of expertise in satisfying customer orders, and diversity of techniques and tools (e.g., vehicle types) add to the amount of uncertainty in organizational task performance. The difference in information processing power is so stark that it results in an information asymmetry between the AIS and human technical core members (Rosenblat 2018; Rosenblat and Stark 2016).

The characterization that NHKWs need only possess information processing power commensurate with some HKWs fits with studies that generally indicate that HKWs prefer to retain complex, non-routinized work that draws significantly upon their expertise. Strategic planning, partnership development, workforce shaping, and internal research and development investment decision-making represent the types of work HKWs generally want to retain, while NHKWs perform simpler and more routine work, such as performing initial reviews of job applicant packages (Baumann and Wu 2023; Choudhary et al. 2023; Tinguely et al. 2023; Iansiti and Lakhani 2020). Furthermore, this representation acknowledges NHKWs might need to develop additional skills and mature in performance over time, akin to HKWs. While more capable AIS approximate and even exceed HKW information processing power, less capable AIS, such as robotic process automation systems and automated workflows, lack the information processing and computational power needed for employment as NHKWs.

Second, NHKWs perform predominantly knowledge work, not service work. This attribute is one that

[3] Deliveroo and Uber Eats are food delivery companies, and Lyft and Uber are rideshare companies; studies generally recognize the four firms for their strategic use of AIS (Burton et al. 2021; Lee et al. 2015; Rosenblat 2018; Rosenblat and Stark 2016). This discussion treats each firm as using a single AIS to perform the organizational tasks described; this seems reasonable because of the extent to which the firms have systematically integrated the AIS into their organizational technologies, which is described subsequently.

distinguishes NHKWs from intelligent robots and other AIS generally used in automobile assembly and warehouse operations (Bartoš et al. 2021; Blake 2023; Burton et al. 2021; Davies et al. 2023). *Knowledge work* is characterized by applying knowledge to knowledge, such as in decision-making, and generating knowledge, such as the result of scientific research activities (Drucker 1988, 1993). *Service work*, on the other hand, involves using knowledge for largely standardized work, such as in automobile assembly (Bartoš et al. 2021; Drucker 1993). This criterion is essential: an AIS cannot be a NHKW unless it performs mostly knowledge work tasks, such as making decisions on behalf of an organization (Mortimore et al. 2023a, 2023b; Drucker 1988, 1993). If the same AIS, with the same capabilities, is tasked with performing mainly service work, it is a service worker.

Organizational decision-making is a quintessential form of knowledge work. Choosing between options that directly impact organizational performance necessitates applying knowledge of an organization's technology to knowledge of a continuum of outcomes (Drucker 1988, 1993; Perrow 1967). AIS already perform knowledge work in food delivery firms, such as Deliveroo and Uber Eats, and rideshare firms, including Lyft and Uber (Iansiti and Lakhani 2020; Lee et al. 2015; O'Connor 2016; Rosenblat and Stark 2016). In each organization, AIS dynamically determine compensation levels, offer performance incentive awards, and mete out work suspensions and terminations—all of which affect organizational performance and stakeholder value generation—autonomously (Lee 2018; Rosenblat 2018; Rosenblat and Stark 2016). The nature of this work contrasts starkly with the service work performed by robotic systems executing generally routinized activities in automobile assembly and warehouse operations (Bartoš et al. 2021; Blake 2023; Burton et al. 2021; Davies et al. 2023). Notably, all organizations perform some degree of knowledge work; therefore, limitations associated with the cognitive performance of HKWs generally condition the performance of all organizations (Drucker 1993; Kahneman 2013; Simon 1973). Assigning AIS to perform relevant knowledge work, in lieu of HKWs, can assist organizations to move beyond performance limitations associated with human-centric systems (Burton et al. 2020; Wang et al. 2016; Willcox and Rosenberg 2019).

Third, NHKWs are employed at the task, not activity, level. Tasks are fundamental to organizational design, technologies, and strategy (Mintzberg 1993; Perrow 1967): tasks represent significant sets of activities essential to an organization accomplishing its strategy (Lawrence and Lorsch 1967; Levitt et al. 1994; Nadler and Tushman 1988). More simply, tasks are major organizational functions that significantly affect mission accomplishment and goal attainment. Task design involves considering the degree of routineness, interdependence, and uncertainty associated with the work, along with the availability of needed technê, methods, tools, and technical core members. In other words, task design entails engineering an organizational technology as a complex system, including reward mechanisms to induce desired behaviors (Galbraith 1977; Nadler and Tushman 1988; Thompson 1967). The perspective that organizations are largely human-centric systems implies that task designs assume a human performer and incorporate limitations associated with human performance (Burton et al. 2021; Carley and Gasser 1999; Nadler and Tushman 1988).

Consequently, human-centric task designs effectively limit the extent to which AIS can impact organizational performance and stakeholder value generation. This is particularly problematic when AIS are more capable than humans in performing a task: human-centric task designs effectively undermine an organization's ability to gain as much from its investments in AIS as it might. Therefore, organizations might need to design tasks to take greater advantage of AIS capabilities to more fully reap the benefits that AIS offer (Murray et al. 2021; Narayanan et al. 2022; Parker and Grote 2022; von Krogh 2018) and strengthen returns on organizational investments in AIS (Arrow 1974; Burton et al. 2021; Nadler and Tushman 1988).

Coordinating the employment of resources is a crucial task in firms with strategies that depend upon rapidly responding to variable and geographically distributed customer orders. Deliveroo and Uber Eats need to continuously anticipate, monitor, and act upon a set of dynamic parameters, when assigning delivery personnel to pick up and deliver food orders, and reassigning delivery orders because an individual fails to respond in a timely manner or declines a work assignment (O'Connor 2016; Rosenblat 2018). Both organizations employ AIS to assess and predict factors, such as order volumes, the availability of delivery personnel, and the geographic distributions of restaurants from which delivery personnel will need to pick up orders and the associated delivery locations (O'Connor 2016; Rosenblat 2018; Rosenblat and Stark 2016). The AIS use this information to preposition delivery personnel, assign orders to delivery personnel, track delivery status and assess performance, and influence the number of delivery personnel available across entire cities. Rideshare organizations, such as DiDi, Lyft, and Uber, also employ AIS to perform similar tasks (Iansiti and Lakhani 2020; Lee et al. 2015; Rosenblat 2018). Importantly, Deliveroo, Uber Eats, Lyft, and Uber purposefully designed their organizational technologies to take advantage of the information processing power of AIS, which generally exceeds that of HKWs (Carley and Gasser 1999; Kahneman 2013; Simon 1973).

Finally, NHKWs are more systematically designed into organizational communication and task structures, which amplifies their contributions to system performance and goal

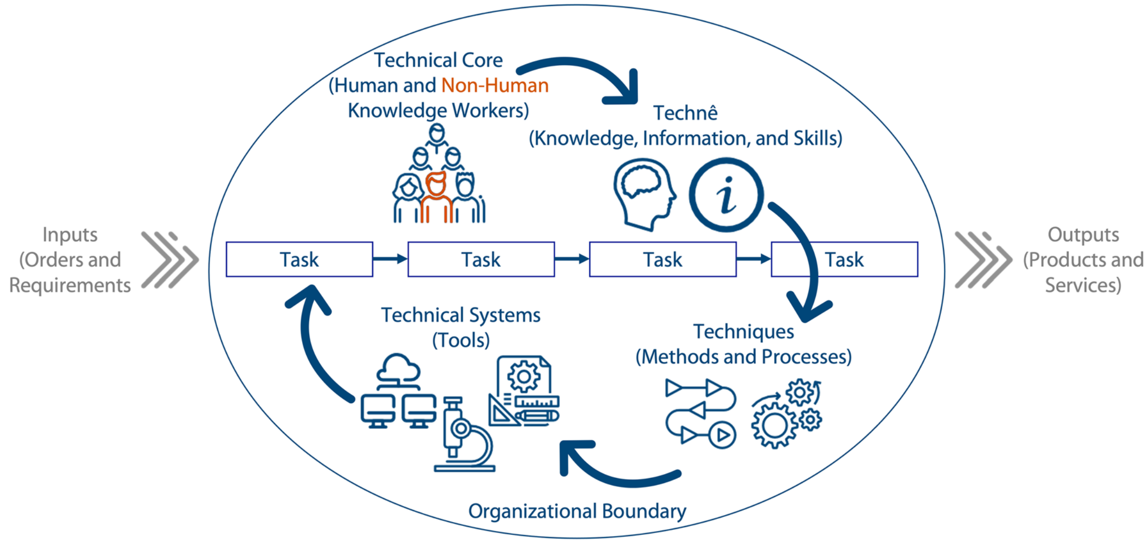


**Fig. 3** NHKWs as technical core members. Designing organizations to employ NHKWs (highlighted in orange) alongside HKW counterparts in the technical core means architecting tasks to take advantage of HKW and NHKW combined capabilities. As members of the technical core, NHKWs can use other system components for organizational goal attainment, similar to their human peers. Adapted from Jansen (2000)

attainment. Simply put, NHKWs are part of the technical core, not apart from it: NHKWs apply their technê and use other organizational system constituents to perform tasks and reify organizational strategy, like their HKW counterparts (see Fig. 3). In comparison, AIS are not as integral to organizational structures and strategies; AIS are effectively tools that technical core members choose when and how to use. The demarcation between NHKWs and AIS, in this regard, likely lies in the extent to which technical core members can choose to work with or use an AIS.

Deliveroo, Uber Eats, Lyft, and Uber employ AIS in their organizational technologies to a degree that is generally characteristic of a NHKW. Deliveroo and Uber Eats food delivery personnel and Lyft and Uber rideshare drivers—all of whom are technical core members—cannot work without interacting directly with the AIS (Lee et al. 2015; O'Connor 2016; Rosenblat 2018). At these four companies, delivery personnel and rideshare drivers report for work via the AIS, receive work assignments from the AIS, report completion of work assignments to the AIS, note problems with deliveries and passengers via the AIS, and find out about events and time periods that could generate extra income from the AIS. Furthermore, delivery personnel and rideshare drivers working with these firms have little, if any, control over the extent to which they interact with the AIS (Lee et al. 2015; O'Connor 2016; Rosenblat 2018; Rosenblat and Stark 2016). Deliveroo, Uber Eats, Lyft, and Uber organizational technology designs integrate AIS so extensively that human technical core members generally have little choice regarding working with the AIS, whatsoever. In contrast, the extent to which human technical core members must interact with AIS to accomplish their work is generally much more limited in automobile assembly and warehouse operations—because of the associated organizational technology designs (Bartoš et al. 2021; Blake 2023; Burton et al. 2021; Davies et al. 2023).

Significantly, more effective NHKW employment necessitates engineering tasks to harness inherent NHKW capabilities because tasks are more directly tied to organizational strategies and, therefore, goal attainment than other organizational technology constituents. More simply, task design drives organizational design and reifies strategy (Burton and Obel 2004; Lawrence and Lorsch 1967; Nadler and Tushman 1988; Mintzberg 1993). Tasks serve as the key building blocks by which organizations realize their strategies. Organizations are inherently complex systems; therefore, task performance is interdependent with the expertise possessed by technical core members and the methods and technical systems used in the technological transformation process (Galbraith 1977; Lawrence and Lorsch 1967; Thompson 1967). Therefore, intentionally designing tasks to employ NHKW capabilities more comprehensively effectively results in designing organizations to employ NHKWs more effectively. Focusing on the inherent and significant relationship between task and organizational designs is at the heart of what Deliveroo, Uber Eats, Lyft, and Uber have done (Frick 2015; Lee et al. 2015; O'Connor 2016; Rosenblat 2018). By designing tasks to employ NHKW-like capabilities more thoroughly, the four companies designed their organizations to reify their individual strategies more robustly.

### A NHKW Boss

Uber's strategy depends upon an organizational technology in which an information processing asymmetry enables Uber to outperform its competitors—an asymmetry largely made possible by a NHKW boss. A *boss* is invested with the authority to make decisions regarding the management and use of organizational resources and compel action (Burton et al. 2023; Malone and Crowston 1991; March and Simon 1958). Bosses process information, choose between alternatives, and assign work, while addressing environmental and task uncertainties (Burton et al. 2023; Cyert and March 1963; Galbraith 1977). In Uber's organizational technology, its boss responds to customers, assigns trips to drivers, analyzes order volumes, coordinates the geographic distribution of drivers, dynamically sets rates and compensation levels, and assesses and manages driver performance—continuously in real-time (Lee et al. 2015; O'Connor 2016; Rosenblat 2018). Uber's strategy necessitates a boss with more robust information processing power than its competitors (Burton et al. 2023; Rosenblat 2018)—and that is unencumbered by cognitive fatigue and other limitations associated with human performance (Carley and Gasser 1999; Simon 1973).

Uber's strategy effectively necessitates the firm move beyond the view of organizations as human-centric systems—and employ a NHKW boss. Uber's AIS conjoins the four attributes needed to be a NHKW: it possesses information processing power that is likely commensurate with some HKWs in the technical core; performs mainly knowledge work  managing use of organizational resources; executes task-level work assignments; and is comprehensively integrated into Uber's organizational system (Burton et al. 2021; Lee et al. 2015; Rosenblat 2018). The work Uber's AIS performs characterizes it is a boss—a NHKW boss and technical core member—and Uber's organizational design allows its NHKW boss to contribute more significantly to performance and stakeholder value generation because the NHKW boss is less constrained by limitations on human performance (Burton et al. 2023; Mintzberg 1973).

Notably, NHKWs encapsulate many technical core roles, including AIS bosses, enhancing the relevancy of the NHKW construct and distinguishing it from other conceptualizations. Studies generally consider AIS as either a teammate or boss, which inadequately addresses cases in which technical core members have multiple roles in an organization. Teammate-focused studies provide invaluable insights into topics, such as divisions of labor, workflow sequencing, and use of specialized knowledge (Agarwal et al. 2018; Glikson and Wooley 2020; Jain et al. 2022; NASEM 2019; Tinguely et al. 2023). Likewise, studies exploring algorithmic managers, such as AI bosses, and the effects of their physical presence, or lack thereof, leadership styles, and computational power on organizational performance are illuminating (Baumann and Wu 2023; Burton et al. 2023; Frick 2015; Lee et al. 2015). However, focusing on AIS as either teammates or bosses limits the relevancy of these studies because they do not overtly consider cases when an AIS might be teammate in one context and a boss in another. Furthermore, these studies generally do not provide a system-level framework, like an organizational technology model, by which managers and organizational designers can more systematically integrate AIS into groups.

Generating stronger organizational performance necessitates moving beyond human-centric designs and management. Numerous studies indicate that a tighter fit between an organization's strategy, technology, and operating environment generally results in stronger performance and stakeholder value generation (Burton and Obel 2004, 2018; Burton et al. 2021; Perrow 1999). Essential to attaining a tight fit is a systematic approach to architecting how organizations use AIS capabilities, as well as mitigating their limitations (Grønsund and Aanestad 2020; Jain et al. 2022; Makarius et al. 2020; Parry et al. 2016; Puranam et al. 2012). By purposefully designing AIS as NHKWs and engineering organizational technologies to employ NHKWs as technical core members, organizations can attain desired performance levels (Burton and Obel 2004; Burton et al. 2021; NASEM 2019).

## Conclusion

Despite growing investments in increasingly sophisticated intelligent robots, autonomous systems, and similar forms of AIS, many organizations are not realizing expected performance gains. Problematic is the predominant view of organizations, grounded in both theory and practice, as mainly human-centric systems—a bias that ill-serves managers and designers of modern organizations and unnecessarily limits group performance. This perspective effectively defines the relationships between HKWs and AIS, resulting in generally less capable task and organizational designs and imposing limitations associated with human performance onto sophisticated artificial agents. Organizational performance is unnecessarily limited, if not diminished, as a result.

Organizations can generate greater performance and stakeholder value by employing NHKWs alongside HKWs in the technical core. This design fundamentally recharacterizes the perceived relationship between HKWs and AIS, enabling organizations to take greater advantage of NHKW capabilities—that can exceed HKW capabilities—in engineering tasks. The resulting organizational technology can produce information processing asymmetries that assist groups better attain their goals and outperform their competitors, as Deliveroo, Uber Eats, Lyft, and Uber are demonstrating. It might be time to set aside a long-standing bias and move beyond a human-centric view of organizations.

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