Received: 12 June 2023 | Accepted: 14 June 2023
DOI: 10.1002/joom.1271

GUEST EDITORIAL

WILEY

Digital transformation in operations management: Fundamental change through agency reversal

1 | INTRODUCTION

The emergence of digital technologies across all aspects of operations management (OM) has enabled shifts in decision making, shaping new operational dynamics and business opportunities. The associated scholarly discussions in information systems (IS) and OM span digital manufacturing (e.g., Roscoe et al., 2019), the digitalization of OM and supply chain management (e.g., Holmström et al., 2019), platform outcomes (e.g., Friesike et al., 2019), and economies of collaboration (e.g., Hedenstierna et al., 2019). For such changes to be successful, however, there is a need for organizations to go beyond the mere adoption of digital technologies. Instead, successful changes are transformational, delving into digital transformation (DT) endeavors (Vial, 2019), which in turn can enable operational improvements in organizational performance (Davies et al., 2017), lead to structural changes in operations processes, and may result in new business models being deployed.

Appropriately, DT endeavors are increasingly treated in both the IS and OM literature as an ongoing process rather than an isolated project with a clear start and finish (e.g., Struijk et al., 2022). Here, we adopt this line of reasoning and specifically treat DT endeavors as: "*the use of digital technologies to evolve operational activities by creating new or transforming existing processes, cultures, and customer experiences to meet changing business and market requirements*." Such a perspective is somewhat distinct from widely adopted definitions of DT in IS and OM (e.g., Vial, 2019), as well as from the strict consideration of radical operational innovation (cf. Hammer, 2004). Specifically, our perspective is neither predicated on "disruption" per se, nor limited by such transformations being fundamentally strategic ones for the focal organization. In other words, DT endeavors can (i) extend into the creation of new organizational processes, (ii) transform existing processes either incrementally or more substantially, (iii) shift decision making with regard to those processes, (iv) enable the consideration of new business models, and (v) largely serve as a source of facilitation and synergy in existing ones. In this special issue, we characterize the specific role of *DT in OM* as follows: *through DT endeavors, digital technologies have the potential to affect OM processes and decision-making with regard to finance, design, production, and the delivery of products, services, or combinations of them.*

The broader OM literature has already set the stage for the consideration of new business models and innovation tournaments that have been extensively influenced by DT endeavors, such as platform services, omnichannel retail, supply chain information exchange, and Internet of Things (IoT)-enabled operations. This line of research can contribute to contemporary and ongoing discussions within the broader field (e.g., Holmström et al., 2019), including the opportunities for organizations to leverage presence in one market into other areas; the emergence of ecosystems that take into consideration all players in the value chain; the appeal of multi-sided platform business models that bring together disparate actors; the value of new data sources when serving new customers; and the importance of artificial intelligence (AI) in the form of advanced algorithmic solutions as a competitive advantage for organizations. Such scholarly discussions can further consider failures caused by the complexity and comprehensiveness of actions that organizations attempt to undertake during DT endeavors (Struijk et al., 2020, 2023).

Empirical research as well as theoretical insights into DT endeavors, therefore, can challenge our established understanding of OM theory and practice, and highlight the importance of organizational dynamics as intertwined with higher levels (Struijk et al., 2022). Our aim here, thus, is to provide an epistemic platform to advance our understanding of how DT endeavors, including the adoption of digital technologies, business model innovations, and innovations in collaboration mechanisms and methods of operations improvement, can affect various aspects of OM. In the discussion that follows, we delineate a review and conceptualization of DT in OM, taking stock of the topic within the field and exploring pathways for moving forward beyond the hype. In doing so, we draw attention to a change in the relationship between humans and technology, where the roles of an agent and a principal are being reversed for the first time in the evolution of the broader IS theory and practice. Specifically, we argue that the transformative nature of DT lies in an *agency reversal* in many organizational processes that are affected by it.

2 | DIGITAL TRANSFORMATION ORIGINS: EVOLUTION OF INFORMATION TECHNOLOGIES IN OPERATIONS

Technology evolution has been a central topic for the broader management literature, due to the transformative effect of technological change on organizations, individuals, and society at large (Grodal et al., 2023). Technology is inherent in OM theory and practice, and its role in the value-adding processes of organizations is crucial to the extent that early management theorists used the word "technology" in place of "process" when discussing what we now know as OM (Thompson, 2017). The evolution of OM, thus, has been tightly linked to the evolution of both physical technology as well as advanced IS, from the invention of the spinning jenny in the early 18th century to modern advanced algorithmic solutions. Our special issue focuses on the latter, within the context of DT and the broader consumerization of digital technologies (Gregory et al., 2018; Struijk et al., 2022). Although we use that term (DT) and argue that the contemporary forms of such technologies bear an exceptional potential for fundamental change, it is still useful to view contemporary technologies within the greater picture of the evolution of organizational IS. In doing so, we see three distinct phases in that evolution as shown in Table 1. This view departs from the idea that the contemporary digital technologies are merely linear extensions of technological evolution, in the sense that they deliver similar benefits as all of the previous technologies such as reducing the costs of data collection, storage, as well as processing, and enable faster and better decision making. Instead, we view the historical development in the role of digital technologies in OM as encompassing three major stages: stand-alone tools, integrated tools, and, contemporaneously, increasingly autonomous tools that have the potential to deliver an unprecedented change in the human-technology relationship, where DT in OM resides. We further discuss these three stages through an elaboration on the leading technologies of the time, providing a brief overview on how various digital technologies have contributed to OM practice.

From the 1970s, when IBM developed the COPICS software package for MRP, until the turn of the millennium, when vendors like Manugistics and i2 marketed advanced planning and scheduling (APS) systems for integrated supply chain optimization, the field of OM has experienced an explosion in the use of IS. In those early days, while MRP systems facilitated the day-to-day planning of manufacturing activities, CAD tools were developed to enable the design of complex components with an unprecedented level of precision. To close the loop, CIM systems emerged to facilitate the use and supervision of automated production tools resulting from the evolution of physical technologies. Although such IS combination provided support for the design, planning, and control loop of OM, each one was function specific. As additional IS got added into the picture, including sales support and procurement systems, the inherent standalone nature of such tools created interface maintenance challenges and quality problems due to redundant databases, incompatible protocols, and data formats. Such challenges, in turn, created the need for the first fundamental change in the role of IS, as depicted in Table 1. Instead of providing function-specific support, digital tools would have to provide comprehensive process-wide support. Additional benefits to such integration would ostensibly include reductions in data and software incompatibilities as well as redundancies (Jacobs & Weston, 2007).

The challenges in such organizational and technology silos were addressed by a new cohort of IS vendors. Aided by the emergence of the client–server information architecture in the 1990s, companies like SAP embraced the challenge of combining the features of the previously function-specific tools into a single, companywide software suite and database. The implementation of these ERP systems turned out to be fraught with challenges, resulting in many well-publicized failures (Davenport, 1998), yet through their inherent support for business-wide integration (Gattiker & Goodhue, 2005) and process standardization (Cotteleer & Bendoly, 2006), they ultimately proved their worth for many organizations (Tenhiälä & Helkiö, 2015). Nevertheless, it also became evident that a single ERP system was not the optimal solution for everyone, and organizations with lesser needs for integration and standardization could perform well with standalone tools (Tenhiälä et al., 2018). To serve the needs of those organizations, a supplemental group of vendors, including Appian and Pegasystems, emerged to resolve the interface and redundancy problems in organizational workflows with a new digital tool called an iBPM system. As a natural extension to the broadening scope of the support of digital tools from individual business functions to entire business processes, a variety of technologies also emerged to support processes that spanned organizational boundaries, including radio-frequency identification for interorganizational product tracking (Bendoly et al., 2007) and APS systems featuring interorganizational supply network planning capabilities (Stadtler, 2005).

By around 2015, the industry began to witness yet another critical development in the use of digital

TABLE 1 Digital evolution in operations management.

	1970–1995	1995–2015	2015 onwards
Role of digital technology	Digital tools provide functional support for humans in OM	Digital tools provide process-wide support for humans in OM	Humans provide support for digital tools in OM
Typical technologies	• Material requirements planning (MRP) • Computer-aided design (CAD) • Computer-integrated manufacturing (CIM)	• Enterprise resource planning (ERP) • Intelligent business process management (iBPM) • Radio-frequency identification (RFID)	• Artificial intelligence (AI)/advanced analytics • Internet of Things (IoT) and Big Data • Advanced self-guided robotics
Genre of technology	**Standalone** tools to aid in function-specific information access	**Integrated** tools for OM across business functions and supply chain entities	**Autonomous** tools to automate OM decision making

technologies. The decades-long trajectory in physical technologies that had led to ever-increasing industrial automation started to find ways to connect directly to digital technologies without a need for a human mediator. Equipped with sensors and algorithmic solutions, advanced robotics reached a new level of autonomy, leading to breakthroughs in a variety of operational settings from warehouse automation to robotic surgeries (Mukherjee & Sinha, 2020) and increasingly in the domain of knowledge-intensive professional services (Spring et al., 2022). Contemporary robotic solutions can relieve human operators from the physical burden of work or enable doing it beyond humanly achievable precision and consistency. In combination with AI, such solutions could assume an increasing proportion of the cognitive burden, as well. To resolve cognitive challenges, AI needs large datasets for training, which are increasingly drawn from constellations of sensors and communication tools known as IoT. While earlier sensor technologies enabled remote monitoring and predictive maintenance of industrial equipment (Persona et al., 2007) as well as real-time sharing of inventory data (Bendoly et al., 2007), current AI-enabled technologies are increasingly capable of proactively controlling and adjusting equipment to optimize maintenance and the timing and quantities of inventory replenishment. Advances in data analytics and in-memory computing (IMC) have critically improved the performance of these digital technologies, kicking off a trend where humans are no longer so much the users of the technology as they are its mere supervisors. In fact, even such a supervisory role could be already questioned, as recent research shows that human interventions and adjustments to the automated decisions of digital tools are more often counterproductive than they are beneficial (e.g., Caro & de Tejada Cuenca, 2023; Ibanez et al., 2018; Kesavan & Kushwaha, 2020). Although the evolution of IS in OM can be viewed through various lenses and perspectives (Grodal et al., 2023), here we emphasize the changing roles in the human-technology relationship (see Table 1) to better understand DT in OM as far more than a simple extrapolation of prior advancements.

3 | SHIFTING DECISION MAKING AND POWER

Concurrent with the emergence of digital technologies, and the rise of DT in OM, has been the appearance of critical questions related to how decision making can be informed or automated, as well as to how the pervasive use of digital technologies and DT impacts individual responsibilities and shifts power among producers, and consumers. Critically, decision support is increasingly provided by both human-driven analysis of such data, and advanced algorithmic solutions. In the extreme, this can represent a significant role reversal in decision-making, positioning non-human actors as decision makers and directing operational moves carried out by humans (Mims, 2021; Schechner, 2017). To best leverage the potential of both actors in advanced decision-making, human-machine interaction needs to be carefully designed (Gante & Angelopoulos, 2022, 2023; Hoberg & Imdahl, 2022). The spectrum from *human driven, technology supported* to *technology driven, human-supported* dynamics—with various degrees of concentration along this spectrum (i.e., a distribution of use)—increasingly characterizes and distinguishes contemporary organizations. This applies to both the case of administrative processes as well as to processes such as order-picking in warehouses (e.g., Sun et al., 2022). Less clear are the costs and benefits of specific levels of *agency reversal* for organizations, for example, when technology usurps the traditional principal role held by humans, or the pressures that these place on the stewardship of the datasets needed to train algorithmic solutions (Angelopoulos et al., 2021).

3.1 | Implications for customers and organizations

The broader management literature has long debated agency. Insights from the early work of Chase (1978), for instance, inspired a wealth of subsequent discussions regarding the varying importance of customers as co-producers, critical to the success of service operations (e.g., Cho et al., 2022; Damali et al., 2022; Dellaert, 2019; Yalley, 2022). Certainly not all service processes benefit from a high degree of customer contact, and thus not all service outcomes are highly reliant on customer (inter) actions; however, some service processes are. As organizations maintain a range of service processes, the degree of customer reliance becomes a distribution bound by various levels of reliance. Further, many service operations that involve customers have a certain level of discretion regarding the quality of service and customer experience provided (Hopp et al., 2007). Organizations are accustomed to understanding—and strategizing around—the customer co-producer role, and they increasingly realize the need of customers to be viewed, in some instances, as partners rather than arms-length entities—not unlike often-referenced close ties between some supplier and buyer organizations.

What organizations have only recently begun to consider, however, is a similar reliance on digital technologies, acting either as advanced agents or as quasi-principals. Such co-production has received limited scholarly attention. Xue et al. (2005) noted a paucity of discussion almost two decades ago, and a contemporary review of the management literature indicates that not much has changed in this regard. Their work discusses the critical, mediating role that particular digital technologies provide to customers positioned in co-producer roles. At this point, digital technologies were already starting to play a role in co-production, albeit still predominantly relegated to a static, or at best responsive, resource status. Currently, many advanced digital technologies can follow rules as well as make their own rules based on their exposure to datasets. In other words, many digital technologies have a capacity to learn, act upon such learning, and give rise to new dynamics. A contemporary example that has taken both academia and industry by storm is ChatGPT, which—according to itself—is a large language model trained to assist in generating human-like text based on provided input.

There are analogies in how learning occurs across a range of digital technologies. Critical to appreciating such learning is a consideration of how digital technologies can leverage what they learn. When customers are considered as co-producers, they are seldom given the opportunity to make impactful changes to operating processes. In a product customization context, for instance, this relates to the use of combinatoric configurations to customize shoes (e.g., model, materials, and colors) without options to add free-form features that alter predefined designs (Randall et al., 2005). Such insights might be gleaned through product and service feedback, but specific and actionable solutions are unlikely to emerge from customers no matter how embedded they are as co-producers. Customers as co-producers, thus, are unlikely to appear beyond the level of agent in a relationship with organizations. Digital technologies pose a striking distinction in this regard, which we depict in Table 2, relative to the potential for customers as co-producers.

There are both upsides and downsides implied by these shifting roles. From an OM perspective, DT clearly has the potential to empower both customers and organizations, however, it can also take some of the decision-making power out of their hands. From a customer empowerment perspective, DT can be operationalized in ways that increase transparency and help customers rationalize benefits and costs/risks associated with a wider array of options (e.g., Clemons et al., 2006). Shifting cognitive burdens onto automated decision support systems can also allow customers to focus on critical aspects of goods and services they might otherwise overlook. That is, digital technologies as an increasingly decisive co-producer can prove a valuable companion to customers in the broader decision-making context of product, and process selection.

This is the case, for example, when it comes to consumer feedback. In the early stages of expansion of digital technologies, the facilitation of IT-supported consumer feedback represented an unprecedented expansion of insight into real-time market performance and emerging trends. Organizations, however, were still reliant on that feedback being voluntarily provided. The increased power of digital technologies, however, can also be used by organizations in place of insights otherwise gained through coordination with customers. With the increasing volume, velocity, and variety of data, advanced algorithmic solutions can now discern shifting interests of customers before they voice their preferences (Zuo et al., 2022, 2023). Currently, every action that a consumer makes, from shopping cart placement to returns, from questions asked of search engines to social media chatter, from click streams to even biometric data, can flow regularly, and be collected, stored, and analyzed.

TABLE 2 Shifting role of digital technology in relation to customers.

	Arms-length	Co-producer	
	Resource	Agent	Principal
Customers	*Traditional* Product purchase or limited engagement service settings	*Conditionally Typical* High service-contact settings where success relies on customer involvement	*Highly Atypical* Extreme MtO/DtO settings where customers fully direct value-added processes
Digital technology	*Traditional* Information support settings constrained by interactivity limits; largely pre-scripted	*Pervasive* Settings where sufficient detail is available to yield responsive, automated support towards actions	*Increasingly Typical* Settings where advanced learning and autonomy permit AI-derived orders/placement/staffing

Insights extracted from such large collections of micro-signals, analyzed through advanced algorithmic solutions, are now far more insightful for retailers than the often biased and sporadic nature of volunteered commentary that online retailers have been accustomed to. The co-producer role has very much shifted from the consumer to the system in this case, giving rise to timely and topical questions: *What does this mean for the value of customer engagement? What does it imply for the value of investments oriented towards customer care?*

If the value of "partnership" shifts away from customers in their limited co-producer capacity and towards that of digital technologies in their exponentially growing capability, then one might anticipate at least some losses in benefits to certain customer sectors (e.g., perhaps those more likely to physically patronize but of less economic value and purchase frequency). We cannot, of course, simply presume that organizations will harness all benefits and opportunities provided by DT, abandoning efforts to foster customer relationships they have long supported, in place of more-lucrative data-intense or data-convenient ones. There are also clear arguments to be made for the value of increased agility that can provide benefits for all the involved parties.

3.2 | Implications for the voice of planners and process managers

A related discussion can be had around human-machine interaction in the domain of forecasting. Many organizations apply advanced algorithmic solutions along with a variety of data sources to create highly granular forecasts, such as those for daily demand per product. A great deal of relevant information including sales history, promotions, transportation costs and condition, weather forecasts, and a host of macro- and micro-economic conditions (borrowing rates, changes in tax policy, etc.) are now readily available in highly structured formats and can be used as inputs for algorithmic solutions. Other information such as local events or income-dependent plant closures may be less structured and are only available to demand planners with "an ear to the ground." As a result, demand planners, who are also ultimately responsible for forecasting performance, often have the opportunity to adjust ostensibly powerful forecasts generated by algorithmic solutions (Perera et al., 2019).

Prior research shows that the extent to which humans add value in forecasting varies greatly (Katsagounos et al., 2021; Khosrowabadi et al., 2022). A critical question, thus, arises as to how to best manage and use the human input in such processes. Rather than risk losses due to well-meaning but potentially biased human judgment, such additional insight might be viewed simply as an additional data stream, feeding into the prediction process as generated by algorithmic solutions, weighing that insight in accordance with its perceived value. Given its variable contribution, as more information becomes available for training and testing algorithmic solutions, the weight given to contextual insights is increasingly constrained (Angelopoulos et al., 2021; Kar et al., 2023). The co-producer role of planners in the production function is, consequently, also diminishing. This, however, also gives rise to an important question for the broader field: *What implications does this hold for the standing of traditional planners in the apparatus of the organization?* One might expect the responsibilities of such agents, or next-generation planners, to transition towards more nuanced organizational considerations that are not positioned for absorption through automation. These might include greater involvement in relationship development internally (e.g., with design teams) or externally (e.g., with strategic partners).

While such value-adding shifts for planners and process managers may seem ideal, they are not forgone conclusions of the DT expansion. As we depict in Table 3, a consideration similar to that regarding customers can be made with regard to the shifting role of operations personnel and digital technologies. Here we can think of the potential for both personnel and technology to emerge from traditional, tactical roles into more strategically relevant positions in the value chain of an organization. For example, algorithmic solutions are becoming increasingly accessible to organizations interested in leveraging IoT for predictive, condition-based maintenance. The use of algorithmic solutions can create a complex criteria structure, such that real-time signals from sensors embedded within equipment can be quickly interpreted to reveal cost-effective cases for preventative maintenance, avoiding impending failures, and corrective maintenance incidents. The mining of process data (e.g., Van der Aalst et al., 2004) can similarly rely on algorithmic solutions to identify opportunities for eliminating unnecessary touchpoints and redundancy loops, some of which may have gone unnoticed for years. In these ways, digital technologies are solidly positioned as an agent capable of "getting things done," on par with operations personnel. Increasingly there are even discussions of algorithmic solutions working far more proactively (i.e., as principals), taking the adjustment of scheduling and processing flow into its own hands, unprompted by a human actor (e.g., Homayouni et al., 2023; Sun et al., 2022), further shifting the balance of agency towards the principal functions in decision making, as we illustrate in Table 3.

A very similar transformation is taking place in the shop-floor. For instance, warehouse workers may be following autonomous robots equipped with algorithmic solutions on their picking route. Such workers may be conducting relatively simple, post-processing operations following robotic ones, such as etching or polishing after fully automated rotation molding and welding. The organizational-behavior implications of these changes in "process leadership," requires attention. The broader OM discipline should be wary of treating human workers as a-emotional agents, like Taylor did more than a century ago, given these shifting co-dependencies.

A challenge in this respect is to manage DT through the involvement of current decision makers, especially since in many planning decisions the value of algorithmic solutions is not yet fully clear. Especially for complex, multi-period, supply-chain planning decisions under uncertainty, algorithmic solutions still lack the ability to take on principal roles. In such cases, with the human still acting as the principal, overcoming *algorithm aversion* is critical, where research suggests that humans need a certain level of autonomy to function well (Dietvorst et al., 2015, 2018). Finally, one important matter to realize is that in operations and supply chains, much of the produced or collected data are proprietary, have strategic value, and are often either generated or—purposefully—manipulated by humans. Many digital technologies rely on such data being reliable, of high quality, and readily available (Struijk et al., 2023). Despite the increasing presence of IoT sensors, current industrial practice shows that such data inputs (in particular so-called master data) require extensive human labor. All of these points come into play as individuals rationalize the trust they place in digital technologies as a part of decision processes (Little, 1970). Just like humans, digital technologies that have been designed to automate—or at least support—decision making are fallible, as well as subject to manipulation and occasionally the source of security concerns (Ou et al., 2022). As isolated sources of decisions, this can prove catastrophic. More virtuously, the combination of human decision makers and digital technologies through a *human-in-the-loop* approach could provide critical checks and balances in highly impactful activities and achieve collaboratively what neither humans nor digital technologies can achieve on their own.

3.3 | Implications for business models and supply chains

Building on the aforementioned arguments, it is also likely that more overarching changes in business models are likely to emerge through DT as digital technologies and algorithmic solutions open up new strategic

TABLE 3 Shifting role of digital technology in relation to internal decision makers.

	Tactical	Strategic	
	Resource	**Agent**	**Principal**
Planners and process managers	*Traditional* Largely monitoring and formulaic execution; business continuation focus	*Conditionally Typical* Providing contextual insight into, and operational solutions aligned with, strategic planning	*Highly Atypical* Extremely integrated functional settings, where operations experts drive strategic decisions
Digital technology	*Traditional* Information support settings, constrained by interactivity limits; reporting/flagging	*Pervasive* Settings where data and technology yield predictive policies and prescriptive insights when needed	*Increasingly Typical* Settings where advanced AI learning and autonomy preemptively pose and enact process adjustments

opportunities. These developments may be accompanied by natural tensions between competitive priorities such as cost, flexibility, and speed (Olsen & Tomlin, 2020), though intelligence emerging through DT may also make possible heretofore unrealized synergies among these priorities. Associated are implications for internal business models and inter-organizational structures (supply chains and vertical partnerships) as we visually depict in Table 4.

Access to data of high volume, velocity, and variety enables organizations to build closer relationships with their customers as they can now better monitor and optimize the use of their assets (Porter & Heppelmann, 2014). Data provided by IoT sensors such as production equipment, cargo containers, or aircraft turbines can enable suppliers to better understand operating conditions, observe use patterns, and identify failures. As a result, organizations can optimize and extend their product offerings in line with the needs of current and new customers. Critically, organizations can also build on the insights gained through enhanced, real-time data and algorithmic solutions to offer value-added services (e.g., preventive maintenance, expansions, upgrades, etc.). Such services can either be monetized directly or offered as free contractual add-ons to improve competitive positioning in the market. Consequently, DT holds the potential to permit facile vertical and horizontal expansion of the interests of organizations. This gives rise to an important question for the broader OM discipline: *What are the implications for smaller supply-chain partners (e.g., contracted maintenance providers)?* Simply because an organization has a greater handle on equipment conditions, it may not be in its best interest to attempt absorbing the work that these smaller entities provide; tighter communication with such providers may be preferable. However, it is possible that this shift in data-enabled decision-making and power could result in a reduction in the variety of external service partners in an "approved/authorized" network.

Beyond enhancements to the core of the existing operations of organizations, DT endeavors can also create opportunities to build entirely new offerings and sell products that customers would not have earlier associated with these organizations. IoT connectivity of household devices is an area poised to inspire shifts of this very kind. Specifically, rather than buying consumables such as washing powder, dishwasher pods, or coffee powder in the supermarket, manufacturers can now analyze consumption patterns and consider the automated anticipatory sales offering of these consumables directly. Whilst this would disintermediate retailers and organizations within the fast-moving consumer goods sector (Hoberg & Herdmann, 2018), such an expansion of offerings is not trivial. To enable such smart-replenishment concepts, organizations need to create new supply-chain architectures as well as last-mile delivery processes, moving beyond middlemen and adding partnerships with new stakeholders to enable economies of scale. Many other examples show the value of data access when building new business models (cf. Uppari et al., 2019).

4 | RELATED CONTRIBUTIONS IN OUR SPECIAL ISSUE

The papers in this special issue exemplify the impact that DT is currently having in OM and the strategic considerations that are rapidly emerging. For instance, Stark et al. (2022) provide a rich discussion of how comprehensive digitalization can be leveraged to replace traditional procedural control. The authors highlight, through example, the potential shift in decision making and power attributable to DT in operational process settings, as well as related impacts across the supply chain. They argue that a key to comprehensive impact is a shift from what they refer to as "procedural syntax" to "object-interactive syntax." In short, the claim is that the manner in which manufacturing

TABLE 4 Business model implications of digital transformation in OM.

	Business model impact		
	Current products	**Value-added services**	**New business model**
Current supply chain architecture	*Traditional* Product purchases only with limited services	*Increasingly Typical* New service offering based on digital interaction with existing supplier-customer networks	*Increasingly Typical* New products or services to existing customer-supplier networks leveraging digital interaction
New supply chain architecture	*Traditional* Product purchases only using new channels and partners	*Pervasive* Service offering enhanced by value-added services offered by new partners integrated for current customers	*Increasingly Typical* Settings with new products or services with new partners or disintermediation

activity is encoded for both managerial discussion purposes, as well as in many associated legacy IS, is essentially as a confederation of separate concepts. Overlap exists only to the degree that information can be transferred at a level of minimal sufficiency between adjacent functions. For example, only certain details of the design process are shared with manufacturing, sourcing, and delivery. Similarly, only minimally sufficient data flows from these functions back to design. This tactic, while meaningful in an era where data transmission and storage were highly limited, is nevertheless baked into many approaches to OM and even pervades modern approaches to technical integration, thus imposing constraints that do not actually represent the digital capabilities of contemporary organizations.

With the advent of digital counterparts, through the addition of part functionality in the design models used in digital equipment contexts, a more interactive syntax arises with pervasive touch points that permits far deeper scopes of automation—automation that is self-correcting in some instances and capable of making the kind of process changes only possible earlier through human diagnosis and intervention. In short, Stark et al. (2022) describe one critical aspect of the conditions under which shifts in digital technology from agent to principal roles become viable. However, the authors also discuss the potential for hybrid, simultaneous use of both forms of encoding, either as a transitional mechanism or as a strategic steady-state. That is, they recognize that a "big-bang" shift from fully procedural to fully object-interactive syntax is likely not a reasonable option for many existing organizations. Rather, they expect procedural and object-interactive syntax to co-exist, with DT likely serving in both agent and distinctly principal roles for the foreseeable future.

A related discussion of encoding-for-integration is demonstrated in Sampson and Pires dos Santos (2023). While the contextual focus of the authors is distinct from that of Stark et al. (2022) in that the concern is that of professional services rather than manufacturing, a very similar message emerges: there are virtues to increased process automation with regards to offloading menial work from employees, as well as reducing cost and increasing speed and consistency. Demonstrated through empirical field data and applied simulation methods, the authors suggest that achieving these gains depends on encoding and open communication. Delegation to automated agency, and in some respects de facto principal decision-making, are described as playing a key role in enabling hybrid DT solutions to these ends, with resulting shifts in control without loss of strategic advantage.

Kude et al. (2023) make an alternative argument, suggesting that greater designation of separability in work can be influential in driving digital outcomes. While integration and delineation may appear to be at odds with one another, they are all part of the same virtuous ideal: a comprehensive, systematic organization of data and workflows. In OM, we have for long appreciated that the extremes of specialization and generalization—depth and breadth—are neither points to which organizations should aspire, but that a healthy and appropriate mix of the two is needed. Consequently, we can also argue that modularization and integration both play critical roles. Indeed, it is hard to imagine one without the other, as "integration" implies deeper connection of elements that have functionality unto themselves but which in combination form a system, and "modularity" implies the ability to compartmentalize specific elements of a larger system in a fashion that permits various forms of reintegration. In the arguments posed by Kude et al. (2023), such an architectural modularity is core to both the success of digital innovation and the wellbeing of those who are tasked with it. Since the discussion of Kude et al. (2023) focuses on the development of software, one might also ask: *Are modularity and integration not only characteristics of effective DT artifacts, but also core DT implementation processes?* Further, *what are the effects of other key architectural patterns, such as cyclicality* (cf. Sosa et al., 2013)*?* If we are to take the insights from the papers in this special issue to heart, the answers would seem to be a resounding "yes" and "we need to find out!"

Lastly, and relating to our discussions of value that can be generated through well designed and integrated approaches to human-technology interaction, Brau et al. (2023) investigate the fusion of human judgment with algorithmic solutions in demand planning. They introduce the innovative approach of Human-Guided Learning. Their approach revolutionizes the training of algorithmic models by incorporating human judgment through an iterative, linear weighting process, resulting in significantly improved accuracy compared to the established integration methods. By highlighting the impact of integration techniques, the study establishes that the effectiveness of human judgment in demand planning hinges on the specific integration method employed, thereby paving the way for further exploration and research in this area. Research such as this should prove instrumental as firms rationalize shifting co-producer and agent/principal roles in a manner that capitalizes on strengths and avoids sidelining contextual intelligence.

5 | OPPORTUNITIES FOR FUTURE RESEARCH

As illustrated in the previous section, our special issue attempt to provide an epistemic platform for advancing our understanding of how DT endeavors, including the adoption of digital technologies, business model innovations, as well as innovations in collaboration mechanisms and methods of operations improvement, can affect various aspects of OM. In doing so, we emphasize the urgency of focusing on the implications of *agency reversal* in many organizational processes affected by the transformative nature of digital technologies. Specifically, we highlight a change in the relationship between humans and technology, where the roles of an agent and a principal are being reversed for the first time in the history of IS. After having delineated a review and conceptualization of DT in OM and taken stock of the topic within the broader field, here we explore pathways for moving forward beyond the hype. Given the growing importance of DT in OM, we see fruitful pathways for future research along the themes discussed in the previous sections that can incorporate conceptual, modeling, and empirical approaches.

5.1 | Customer role and agency reversal

It is clear that one research stream should delve further into the *role of customers* in digitally transformed operational processes. The future role of the customer needs to be fully understood and defined, as critical questions arise around *if* and *where* customers actually see the value of taking a more relevant role in co-creation processes. While DT endeavors can provide customers with more choices and degrees of freedom, the derived utility needs to be quantified. Ideally it would exceed costs of involvement. Similar to the question of where a customer would benefit from customization of car components using 3D printing, the incremental utility of customer involvement as a co-producer can be negligible, relative to incremental effort applied. Another challenge for organizations is the increasing availability of—potentially sensitive—data provided by the customer that needs to be managed and analyzed, raising timely issues regarding the stewardship of such datasets. While there is certainly signal in the oceans of data noise, making these data actionable in OM processes might be hard. For example, after the acquisition of customer-experience software provider Qualtrics, SAP has struggled to use customer data as an input for decisions around improving operations. Research should address such challenges by investigating *which* operations can really benefit from the insights that can be extracted from customer data and *how* this can be done with the aid of advanced algorithmic solutions.

A second related research stream, and fundamental to this guest editorial and special issue, orbits *the concept of agency reversal*. Algorithmic solutions and customers increasingly become involved in organizational decision making, reversing the power structure. As illustrated in the previous sections, we have observed several cases of agency reversal, which can take place at micro (individual), meso (group), and macro (industry) levels. Thus, we envision that the concept of agency reversal can inspire scholarly dialogue and business practice around OM. We call for future research on the conceptualization of agency reversal at the micro, meso, and macro levels, operationalization of this concept in observable empirical contexts, and comparisons and tests of the actual roles of algorithmic solutions and customers in the co-production of decisions.

5.2 | Internal/external planning and business models

A third research avenue focuses on the automation of decision making within organizations, and its impact on *planners and process managers*. Prior research has highlighted the potential of algorithmic solutions for augmenting and even replacing humans in decision making. Here, it is important to investigate how human work can be designed in a way that leverages the strengths of the various players to achieve an *optimal* result for organizations. By "optimal" here we refer to a multidimensional construct since it comprises much more than just the performance outcome of a decision. Other aspects include the efficiency of humans in decision making, in terms of the decision rights given to them but also their motivation to conduct their work. On one hand, prior research has discussed the automation paradox (e.g., Bessen, 2022; Raisch & Krakowski, 2021) that highlights the challenges when automating decision-making: initially, simple decisions can be automated, and the overall workload of humans (and their head count) can be reduced. However, this leaves the remaining humans with the most complex and challenging tasks that require more attention, peak cognitive performance, and continuous problem-solving skills. On the other hand, humans could become less motivated in their role and involvement by just overseeing systems where they perceive that they add limited value. Instead of making decisions at the moment of truth, the role of humans shifts towards preparing algorithmic solutions, ensuring availability of high-quality data, and reviewing performance which for many workers would mean a significant shift in their work content and could also undermine their motivation.

A fourth research stream should revolve around the implications of DT for *Business Models, Supply Chains, and broader implications at industry levels*. Prior studies have highlighted how digital technologies can be used to increase the reliability of information traceability in real time for supply-chain management without human intervention (Cao et al., 2022). Whilst such technologies have the potential to give rise to novel business models, this remains far from the de facto standard of supply-chain management. There are, consequently, opportunities for future research on the implementation and adoption of such architectures that incorporate digital technologies. At the industry level, the advent of DT opportunities has brought about constant change and competition. While leaders in technology-intensive industries may face challenges in advancing new systems due to their associated legacy infrastructures, they are more likely to win the market and gain long-term competitive advantages compared to lagging organizations. On the other hand, organizations that are slower to engage in DT endeavors may find it easier to draw on best practices, but such gains may be temporary and unsustainable (cf. McAfee & Brynjolfsson, 2007). It is important to note that DT is a complex process that involves interdependent clusters of technologies; each technology development can affect many others and change the macro-level of technological revolutions as epochal, societal-scale phenomena (Bodrožić & Adler, 2022). The recent developments in advanced algorithmic solutions showcase how technology can fundamentally change and shift competition in industries that do not necessarily rely on complex operations. However, if operations are complex, distributed, subject to (physical) processing times and lead times, and subject to limited capacity to fulfill operations requirements, the success of DT is much more ambiguous.

In this sense, it is interesting to compare Amazon Web Services (AWS) with Amazon Retail. AWS has digital processes at its core, supported by physical operations in datacenters. Amazon Retail has physical processes at their core—in particular in their fulfillment operations—with digital technologies supporting these processes. The sheer difference in profitability ratios of the two arms of the same company, with AWS much more profitable than Amazon Retail, demonstrates that adopting digital technologies in organizations with extensive physical operations is much more challenging than if the processes are administrative or were already augmented by new digital technologies. While DT can exacerbate competitive effects on the industry level, it can also offer significant innovations that enhance business operations and data-driven decision making. In line with these, therefore, we encourage future research to further elaborate on the role of DT in changing the competitive landscape in industries, with a nuanced perspective when physical assets and physical operations come into play.

5.3 | Ethical considerations

A fifth research direction, related to each of those already outlined, confronts the *ethical implications* surrounding the concept of DT in OM, and more specifically those implications relating to the use of advanced algorithmic solutions within and around organizational settings. The increasing volume, velocity, and variety of data can enable the creation of *value* in organizations but also raises the need for decision makers to re-examine their own *values*. The availability of sensitive data can certainly give rise to concerns related to their stewardship (Angelopoulos et al., 2021) and the possibility for organizations to become honeypots for malicious entities, which could result in devastating outcomes (Ou et al., 2022). Concurrently, as we have alluded to, the advances in performance and accuracy of algorithmic solutions can result in the redundancy of personnel at all organizational levels, creating overloads for the remaining personnel as well as the urgent need for training on a new set of capabilities. Further to these, during a time when organizations, governments, and the society at large are increasingly becoming more sensitive to environmental issues, we should not discount the environmental footprint that the training of advanced algorithmic solutions can have (e.g., Patterson et al., 2022). Broadly speaking, when considering the negative impacts of DT on individuals, society, and environment, ethics play a vital role by offering principles to guide decision-making and behaviors, especially for addressing the potential harm or misuse of information and digital technologies.

As an additional area of study, related to DT and ethics, crowd-sourcing and co-design platforms are also showing momentum within the broader OM literature, redefining both financing and operations. Crowdsourcing platforms, like Kickstarter, can re-organize business and project processes virtually, from start to finish. The phenomenon of crowdsourcing and co-design platforms started in early 2010, but their penetration reached significant scale in early 2020. Such platforms enable collective efforts by consumers, who collaboratively network and pool labor, resources, and the corresponding ecosystems together within the platform. Platform ecosystems, therefore, represent a further major step in the critical evolution of consumers' roles, shifting decision-making as well as power and reshaping dynamics in business operations. Beyond crowdsourcing, digital platforms that have established disruptive ecosystems are shaping new ways for matching supply and demand. In ridesharing, for instance, platforms like Uber match riders with drivers. In meal delivery, platforms like JustEast match restaurants with consumers. Similar platform ecosystems have emerged for digital freight forwarding, such as Sennder, as well as for digital wholesaling, such as Wasoko. Such platforms allow for economies of scale to be realized without the demand and supply sides gaining size themselves, giving rise to novel value chains. *What are the ethical considerations* *when it comes to sharing value created from data used in such matching?* Future research endeavors, therefore, could further reflect on the notion of value co-creation within the context of platform ecosystems and address questions of *how* and *to what extent* the involved actors can create and capture value. Such future research endeavors can expand to both digital-native and pre-digital organizations, to support them in choosing the right DT strategy (Mithas & Rust, 2021; Struijk et al., 2023).

Such future research into DT in OM also offers opportunities for various methodological approaches. For instance, the OM field has recently opened up to intervention-based research (Chandrasekaran et al., 2020), an approach that has been forged and well adopted in the IS field. Therefore, the questions surrounding DT endeavors can benefit from intervention-based approaches such as action research (e.g., Struijk et al., 2023), action design research (Sein et al., 2011), and design science (e.g., Gregor & Hevner, 2013). Concurrently, as the IS field increasingly recognizes the value of qualitative research as well as historical and archival datasets (Monteiro et al., 2022), we can also benefit from interpretivist approaches when studying topics at the intersection of IS and OM, such as the ways that DT endeavors unfold over time (e.g., Struijk et al., 2022). Finally, as the implementation of advanced algorithmic solutions holds the potential of transforming OM (Mithas et al., 2022), future research should further explore questions related to their adoption and retention. The topic provides opportunities for experiment-based approaches that, in the context of OM, can further explore the trust of decision-makers in the suggestions of algorithmic solutions (q.v., Little, 1970).

6 | CONCLUDING REMARKS

Our special issue showcases how OM is being transformed by the implementation and adoption of novel digital technologies and how DT is increasingly becoming a key concept across the broader OM research and practice. The associated articles of the special issue address the importance of the topic, while in this guest editorial we bridge the IS and OM disciplines to further conceptualize the shifting role of agency in decision making due to the adoption of digital technologies. We do so both conceptually as well as, more specifically, with regard to advanced algorithmic solutions. An examination of the literature situated at the intersection of IS and OM suggests that this is only the beginning of what is likely to be an ongoing consideration of role shifts between human and technology agents and principals. Such an agency reversal brings forward novel issues for OM practice, new business models, and renovated supply chain architectures, as well as increased industry competition, and vital ethical considerations. To carefully study such a novel phenomenon, we need to approach it with new perspectives. The advances in algorithmic solutions have showcased that, when trained well, they can provide us with the right answers; going forward, it is more imperative than ever that we ask the right questions.

ACKNOWLEDGMENTS

The authors would like to thank the associate editors and reviewers of the Special Issue for their great service, as well as the co-Editors-in-Chief, Suzanne de Treville and Tyson Browning, for their valuable comments for this guest editorial and their continuous support for the Special Issue.

Spyros Angelopoulos[1]
Elliot Bendoly[2]
Jan Fransoo[3]
Kai Hoberg[4]
Carol Ou[3]
Antti Tenhiälä[5]

[1]*Durham University, Durham, UK*
[2]*Ohio State University, Columbus, Ohio, USA*
[3]*Tilburg University, Tilburg, The Netherlands*
[4]*Kühne Logistics University, Hamburg, Germany*
[5]*IE University, Madrid, Spain*

Correspondence
Spyros Angelopoulos, Durham University, Durham, UK.
Email: spyros.angelopoulos@durham.ac.uk

Handling Editors: Tyson Browning and Suzanne de Treville

ORCID

Spyros Angelopoulos https://orcid.org/0000-0002-8165-8204
Elliot Bendoly https://orcid.org/0000-0002-0158-8403
Jan Fransoo https://orcid.org/0000-0001-7220-0851
Kai Hoberg https://orcid.org/0000-0003-2835-572X
Antti Tenhiälä https://orcid.org/0000-0003-2890-0003

REFERENCES

Angelopoulos, S., Brown, M., McAuley, D., Merali, Y., Mortier, R., & Price, D. (2021). Stewardship of personal data on social networking sites. *International Journal of Information Management*, *56*, 102208.

Bendoly, E., Citurs, A., & Konsynski, B. (2007). Internal infrastructural impacts on RFID perceptions and commitment: Knowledge, operational procedures, and information-processing standards. *Decision Sciences*, *38*(3), 423–449.

Bessen, J. (2022). 5 The automation paradox. In *The new goliaths* (pp. 70–82). Yale University Press.

Bodrožić, Z., & Adler, P. S. (2022). Alternative futures for the digital transformation: A macro-level Schumpeterian perspective. *Organization Science*, *33*(1), 105–125.

Brau, R., Aloysius, J., & Siemsen, E. (2023). Demand planning for the digital supply chain: How to integrate human judgment and predictive analytics. *Journal of Operations Management*, *69*(6), 965–982. https://doi.org/10.1002/joom.1257

Cao, Y., Yi, C., Wan, G., Hu, H., Li, Q., & Wang, S. (2022). An analysis on the role of blockchain-based platforms in agricultural supply chains. *Transportation Research Part E: Logistics and Transportation Review*, *163*, 102731.

Caro, F., & de Tejada Cuenca, A. S. (2023). Believing in analytics: Managers' adherence to price recommendations from a DSS. *Manufacturing & Service Operations Management*, *25*, 524–542.

Chandrasekaran, A., de Treville, S., & Browning, T. (2020). *Intervention-based research (IBR) – What, where, and how to use it in operations management* (Vol. 66, pp. 370–378). Wiley Online Library.

Chase, R. B. (1978). Where does the customer fit in a service operation? *Harvard Business Review*, *56*(6), 137–142.

Cho, W., Min, D.-J., & Dresner, M. (2022). The impact of predicted quality and customer cost on quality assurance behavior. *International Journal of Operations & Production Management*, *42*, 409–439.

Clemons, E. K., Gao, G. G., & Hitt, L. M. (2006). When online reviews meet hyperdifferentiation: A study of the craft beer industry. *Journal of Management Information Systems*, *23*(2), 149–171.

Cotteleer, M. J., & Bendoly, E. (2006). Order lead-time improvement following enterprise information technology implementation: An empirical study. *MIS Quarterly*, *30*, 643–660.

Damali, U., Fredendall, L. D., Miller, J. L., Moore, D., & Dye, C. J. (2022). Enhancing patient participation in healthcare operations through patient training and education using the theoretical lens of media synchronicity. *Decision Sciences*, *53*(4), 750–770.

Davenport, T. H. (1998). Putting the enterprise into the enterprise system. *Harvard Business Review*, *76*(4), 121–131.

Davies, R., Coole, T., & Smith, A. (2017). Review of socio-technical considerations to ensure successful implementation of industry 4.0. *Procedia Manufacturing*, *11*, 1288–1295.

Dellaert, B. G. (2019). The consumer production journey: Marketing to consumers as co-producers in the sharing economy. *Journal of the Academy of Marketing Science*, *47*(2), 238–254.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*(1), 114–126.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science*, *64*(3), 1155–1170.

Friesike, S., Flath, C. M., Wirth, M., & Thiesse, F. (2019). Creativity and productivity in product design for additive manufacturing: Mechanisms and platform outcomes of remixing. *Journal of Operations Management*, *65*(8), 735–752.

Gante, S., & Angelopoulos, S. (2022). Paving the way toward human-algorithm interactions: Understanding AI-CAD adoption for breast cancer detection. In *The proceedings of the European conference in information systems* (ECIS).

Gante, S., & Angelopoulos, S. (2023). Information overload in the age of algorithmic solutions: The effect of patients' information processing capability on their perceived quality of healthcare. In *The proceedings of the UKAIS conference, Kent, UK*.

Gattiker, T. F., & Goodhue, D. L. (2005). What happens after ERP implementation: Understanding the impact of interdependence and differentiation on plant-level outcomes. *MIS Quarterly*, *29*, 559–585.

Gregor, S., & Hevner, A. R. (2013). Positioning and presenting design science research for maximum impact. *MIS Quarterly*, *37*, 337–355.

Gregory, R. W., Kaganer, E., Henfridsson, O., & Ruch, T. J. (2018). IT consumerization and the transformation of IT governance. *MIS Quarterly*, *42*(4), 1225–1253.

Grodal, S., Krabbe, A. D., & Chang-Zunino, M. (2023). The evolution of technology. *Academy of Management Annals*, *17*(1), 141–180.

Hammer, M. (2004). Deep change: How operational innovation can transform your company. *Harvard Business Review*, *82*, 84–93.

Hedenstierna, C. P. T., Disney, S. M., Eyers, D. R., Holmström, J., Syntetos, A. A., & Wang, X. (2019). Economies of collaboration in build-to-model operations. *Journal of Operations Management*, *65*(8), 753–773.

Hoberg, K., & Herdmann, C. (2018). Get smart (about replenishment). *Supply Chain Management Review*, *22*(1), 12–19.

Hoberg, K., & Imdahl, C. (2022). How to design human–machine interaction in next-generation supply chain planning. In *Global logistics and supply chain strategies for the 2020s: Vital skills for the next generation* (pp. 67–82). Springer.

Holmström, J., Holweg, M., Lawson, B., Pil, F. K., & Wagner, S. M. (2019). *The digitalization of operations and supply chain management: Theoretical and methodological implications* (Vol. 65, pp. 728–734). Wiley Online Library.

Homayouni, S. M., Fontes, D. B., & Gonçalves, J. F. (2023). A multi-start biased random key genetic algorithm for the flexible job shop scheduling problem with transportation. *International Transactions in Operational Research*, *30*(2), 688–716.

Hopp, W. J., Iravani, S. M., & Yuen, G. Y. (2007). Operations systems with discretionary task completion. *Management Science*, *53*(1), 61–77.

Ibanez, M. R., Clark, J. R., Huckman, R. S., & Staats, B. R. (2018). Discretionary task ordering: Queue management in radiological services. *Management Science*, *64*(9), 4389–4407.

Jacobs, F. R., & Weston, F. C., Jr. (2007). Enterprise resource planning (ERP) – A brief history. *Journal of Operations Management*, *25*(2), 357–363.

Kar, A. K., Angelopoulos, S., & Rao, H. R. (2023). Big data-driven theory building: Philosophies, guiding principles, and common traps. *International Journal of Information Management*, *71*(102661), 1–7.

Katsagounos, I., Thomakos, D. D., Litsiou, K., & Nikolopoulos, K. (2021). Superforecasting reality check: Evidence from a small pool of experts and expedited identification. *European Journal of Operational Research*, *289*(1), 107–117.

Kesavan, S., & Kushwaha, T. (2020). Field experiment on the profit implications of merchants' discretionary power to override data-driven decision-making tools. *Management Science*, *66*(11), 5182–5190.

Khosrowabadi, N., Hoberg, K., & Imdahl, C. (2022). Evaluating human behaviour in response to AI recommendations for judgemental forecasting. *European Journal of Operational Research*, *303*(3), 1151–1167.

Kude, T., Foerderer, J., Mithas, S., & Heinzl, A. (2023). How deadline orientation and architectural modularity influence software quality and job satisfaction. *Journal of Operations Management*, *69*(6), 941–964. https://doi.org/10.1002/joom.1230

Little, J. D. (1970). Models and managers: The concept of a decision calculus. *Management Science*, *16*(8), B-466–B-485.

McAfee, A., & Brynjolfsson, E. (2007). Dog eat dog. *The Wall Street Journal*. https://www.wsj.com/articles/SB117735476945179344

Mims, C. (2021). Amazon's new CEO, Andy Jassy, can either help workers and sellers – Or automate them away. *The Wall Street Journal*. https://www.wsj.com/articles/amazons-new-ceo-can-either-help-workers-and-sellersor-automate-them-away-11612587602

Mithas, S., Chen, Z. L., Saldanha, T. J., & De Oliveira Silveira, A. (2022). How will artificial intelligence and industry 4.0 emerging technologies transform operations management? *Production and Operations Management*, *31*(12), 4475–4487.

Mithas, S., & Rust, R. T. (2021). How to choose the right strategy for digital transformation. *Management and Business Review*, *1*(3), 66–71.

Monteiro, E., Constantinides, P., Scott, S., Shaikh, M., & Burton-Jones, A. (2022). Editor's comments: Qualitative methods in IS research: A call for phenomenon-focused problematization. *MIS Quarterly*, *46*(4), iii–xix.

Mukherjee, U. K., & Sinha, K. K. (2020). Robot-assisted surgical care delivery at a hospital: Policies for maximizing clinical outcome benefits and minimizing costs. *Journal of Operations Management*, *66*(1–2), 227–256.

Olsen, T. L., & Tomlin, B. (2020). Industry 4.0: Opportunities and challenges for operations management. *Manufacturing & Service Operations Management*, *22*(1), 113–122.

Ou, C. X., Zhang, X., Angelopoulos, S., Davison, R. M., & Janse, N. (2022). Security breaches and organization response strategy: Exploring consumers' threat and coping appraisals. *International Journal of Information Management*, *65*, 102498.

Patterson, D., Gonzalez, J., Hölzle, U., Le, Q., Liang, C., Munguia, L.-M., Rothchild, D., So, D. R., Texier, M., & Dean, J. (2022). The carbon footprint of machine learning training will plateau, then shrink. *Computer*, *55*(7), 18–28.

Perera, H. N., Hurley, J., Fahimnia, B., & Reisi, M. (2019). The human factor in supply chain forecasting: A systematic review. *European Journal of Operational Research*, *274*(2), 574–600.

Persona, A., Regattieri, A., Pham, H., & Battini, D. (2007). Remote control and maintenance outsourcing networks and its applications in supply chain management. *Journal of Operations Management*, *25*(6), 1275–1291.

Porter, M. E., & Heppelmann, J. E. (2014). How smart, connected products are transforming competition. *Harvard Business Review*, *92*(11), 64–88.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192–210.

Randall, T., Terwiesch, C., & Ulrich, K. T. (2005). Principles for user design of customized products. *California Management Review*, *47*(4), 68–85.

Roscoe, S., Cousins, P. D., & Handfield, R. (2019). The microfoundations of an operational capability in digital manufacturing. *Journal of Operations Management*, *65*(8), 774–793.

Sampson, S., & Pires dos Santos, R. (2023). Reengineering professional services through automation, remote outsourcing, and task delegation. *Journal of Operations Management*, *69*(6), 911–940. https://doi.org/10.1002/joom.1268

Schechner, S. (2017). Meet your new boss: An algorithm. *The Wall Street Journal*. https://www.wsj.com/articles/meet-your-new-boss-an-algorithm-1512910800

Sein, M. K., Henfridsson, O., Purao, S., Rossi, M., & Lindgren, R. (2011). Action design research. *MIS Quarterly*, *35*, 37–56.

Sosa, M. E., Mihm, J., & Browning, T. R. (2013). Linking cyclicality and product quality. *Manufacturing & Service Operations Management*, *15*(3), 473–491.

Spring, M., Faulconbridge, J., & Sarwar, A. (2022). How information technology automates and augments processes: Insights from artificial-intelligence-based systems in professional service operations. *Journal of Operations Management*, *68*(6–7), 592–618.

Stadtler, H. (2005). Supply chain management and advanced planning – Basics, overview and challenges. *European Journal of Operational Research*, *163*(3), 575–588.

Stark, A., Ferm, K., Hanson, R., Johansson, M., Khajavi, S., Medbo, L., Öhman, M., & Holmström, J. (2022). Hybrid digital manufacturing: Capturing the value of digitalization. *Journal of Operations Management*, *69*(6), 890–910. https://doi.org/10.1002/joom.1231

Struijk, M., Angelopoulos, S., Ou, C., & Davison, R. M. (2020). Influencing information quality: Evidence from a military organization. In *European conference on information systems*.

Struijk, M., Angelopoulos, S., & Ou, C. X. (2022). Emergence and evolution of digital transformation: A morphogenetic approach. *Academy of Management Proceedings*. https://doi.org/10.5465/AMBPP.2022.11244abstract

Struijk, M., Angelopoulos, S., Ou, C. X., & Davison, R. M. (2023). Navigating digital transformation through an information quality strategy: Evidence from a military organization. *Information Systems Journal*, *33*(4), 912–952.

Sun, J., Zhang, D. J., Hu, H., & Van Mieghem, J. A. (2022). Predicting human discretion to adjust algorithmic prescription: A large-scale field experiment in warehouse operations. *Management Science*, *68*(2), 846–865.

Tenhiälä, A., & Helkiö, P. (2015). Performance effects of using an ERP system for manufacturing planning and control under dynamic market requirements. *Journal of Operations Management*, *36*, 147–164.

Tenhiälä, A., Rungtusanatham, M. J., & Miller, J. W. (2018). ERP system versus stand-alone enterprise applications in the mitigation of operational glitches. *Decision Sciences*, *49*(3), 407–444.

Thompson, J. D. (2017). *Organizations in action: Social science bases of administrative theory*. Routledge.

Uppari, B. S., Popescu, I., & Netessine, S. (2019). Selling off-grid light to liquidity-constrained consumers. *Manufacturing & Service Operations Management*, *21*(2), 308–326.

Van der Aalst, W., Weijters, T., & Maruster, L. (2004). Workflow mining: Discovering process models from event logs. *IEEE Transactions on Knowledge and Data Engineering*, *16*(9), 1128–1142.

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, *28*(2), 118–144.

Xue, M., Hein, G. R., & Harker, P. T. (2005). Consumer and co-producer roles in e-service: Analysing efficiency and effectiveness of e-service designs. *International Journal of Electronic Business*, *3*(2), 174–197.

Yalley, A. A. (2022). Customer readiness to co-production of mobile banking services: A customer-only co-production perspective. *Journal of Financial Services Marketing*, *27*(2), 81–95.

Zuo, M., Angelopoulos, S., Liang, Z., & Ou, C. X. (2022). Blazing the trail: Considering browsing path dependence in online service response strategy. *Information Systems Frontiers*, 1–15. Forthcoming.

Zuo, M., Angelopoulos, S., Ou, C. X. J., Liu, H., & Liang, Z. (2023). Optimization of dynamic product offerings on online marketplaces: A network theory perspective. *Journal of Management Information Systems*, Forthcoming.