Journal of Business Research 168 (2023) 114236

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

The cold-start problem in nascent AI strategy: Kickstarting data network effects

Arnd Vomberg [a], Nico Schauerte [b], Sebastian Krakowski [c], Claire Ingram Bogusz [d,c], Maarten J. Gijsenberg [e,*], Alexander Bleier [f]

[a] University of Mannheim, L9, 7, 68131 Mannheim, Germany
[b] Vrije Universiteit Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, the Netherlands
[c] House of Innovation – Stockholm School of Economics, Saltmätargatan 13, 113 59 Stockholm, Sweden
[d] Department of Informatics and Media – Uppsala University, Ekonomikum, Kyrkogårdsgatan 10, 751 20 Uppsala, Sweden
[e] Department of Marketing – Faculty of Economics and Business – University of Groningen, PO Box 800, 9700 AV Groningen, the Netherlands
[f] Frankfurt School of Finance & Management GmbH, Adickesallee 32-34, 60322 Frankfurt am Main, Germany

ARTICLE INFO

Keywords:
Artificial intelligence
Cold-start problem
Data strategy
Network effects
Value creation

ABSTRACT

While many artificial intelligence (AI) strategies are successful, countless others fail. Why do some strategies succeed while others fail? We adopt a network effects (NEs) perspective to conceptualize AI strategies, highlighting the AI context's specifics. We argue that nascent AI strategies' success depends on data NEs: companies establishing a functional "running system" to capitalize on these effects. However, this presents a challenge known as the cold-start problem (CSP), which involves initiating and accelerating a virtuous cycle: more data benefits the AI system, enhancing performance, which then attracts more data. In this paper, we examine the CSP in nascent AI strategy, exploring how it can be understood in terms of its technological and business dimensions and ultimately be overcome to kick-start a virtuous cycle of data NEs. By drawing insights from existing literature and practitioner interviews, we present a research agenda to encourage further investigation into overcoming the CSP.

1. Introduction

Both academic (e.g., Agrawal et al., 2018; Berente et al., 2021) and industry (Bughin et al., 2018; Ransbotham et al., 2022) research highlights the economic and organizational benefits of artificial intelligence (AI). Investigators increasingly understand the reasons for these advances in terms of network effects (NEs) (e.g., Clough & Wu, 2022; Gregory et al., 2021; Haftor et al., 2021), which provide exponential benefits from increased data volume and representativeness, known as data NEs. The acquisition of more data by an organization leads to increased value creation for both the organization and its customers, enabling increased data inflows to fuel a virtuous cycle. Thereby, value refers to utility—both for members of the organization and for customers, collectively referred to as "users"—which in turn can increase effectiveness or be monetized.

Data NEs can help explain the benefits of AI and the emergence of winner-take-all dynamics in AI markets (Brynjolfsson & McAfee, 2014). They may also offer a basis upon which to understand—and overcome—early-stage hurdles as part of a larger AI implementation strategy relating to the application of AI technologies. We refer to this early and preparatory period as the nascent AI strategy phase. During this phase, overcoming the cold-start problem (CSP)[1]—that is, a company's inability to obtain data of sufficient quality and quantity to allow for the mobilization of additional data to spur data NEs (often by attracting a sufficiently large user base; Lam et al., 2008)—is a necessary precondition for subsequent AI-led value creation.

The difficulty in establishing data NEs is evident in two recent and well-documented failed cases. First, attempts to build machine learning–based predictive tools to help diagnose COVID-19 during the pandemic failed from a combination of a lack of early access to

* Corresponding author.
E-mail addresses: Vomberg@uni-mannheim.de (A. Vomberg), N.Schauerte@vu.nl (N. Schauerte), Sebastian.Krakowski@hhs.se (S. Krakowski), Claire.Ingrambogusz@im.uu.se (C. Ingram Bogusz), M.J.Gijsenberg@rug.nl (M.J. Gijsenberg), A.Bleier@fs.de (A. Bleier).

[1] Synonymous terms include the "bootstrap problem" among infrastructures (Grisot et al., 2014) and the "chicken-and-egg problem" among digital platforms (Eisenmann et al., 2006).

https://doi.org/10.1016/j.jbusres.2023.114236
Received 1 December 2022; Received in revised form 31 May 2023; Accepted 17 August 2023
Available online 26 August 2023

pandemic data and unclear assumptions about the data (Heaven, 2021). The second example is Amazon.com's attempt to use AI for recruitment, which failed as a result of inadequate data, leading to biased and discriminating outcomes (Dastin, 2018).

Understanding the CSP and how (if at all) it can be overcome can help explain why, even though more than 80% of Fortune 500 chief executive officers indicate that AI will be extremely critical for their business (Murry, 2017), only one in 10 organizations reports significant financial benefits from an AI strategy (Ransbotham et al., 2022) (i.e., by adopting and implementing AI in value creation[2]), and relatively few companies have adopted AI so far (Acemoglu et al., 2022). Overcoming the CSP is necessary for companies to initiate the virtuous cycles for which data NEs have become known (Hagiu & Wright, 2020). Thus, the nascent stage of an AI strategy is crucial for organizational performance. We aim to investigate AI as a technology capable of learning autonomously by asking the following questions: What is the role of data NEs in nascent AI strategy? How can data NEs help explain the prevalent CSP? And how can companies overcome the CSP?

We draw from literature on information systems, strategic management, and marketing to provide insights into the managerial challenges of AI strategy, develop a network perspective on AI-led value creation, and analyze the technological and business dimensions of the CSP in nascent AI strategy. We further illustrate these points with insights from interviews with experts in AI strategy.

We contribute in three ways to the emerging literature on AI in organizations and particularly knowledge engineering, a focal subfield of AI that attempts to mimic the judgment and behavior of human experts (e.g., Csaszar & Steinberger, 2022). First, we extend prior research that links NEs to the AI strategy context (e.g., Gregory et al., 2021). We consider AI's characteristics and identify focal peculiarities of data NEs. Second, we extend the current understanding of the CSP to include both technological (i.e., literature on recommender systems and information systems literature in general) and business (i.e., data NEs and theory on NEs and AI-led value creation) dimensions, which is appropriate for this complex interplay between humans and technology (e.g., Berente et al., 2021). We identify approaches to overcome the CSP associated with nascent AI strategy. Third, to the best of our knowledge, no multidisciplinary discussion of nascent AI strategy exists. Such a perspective is necessary, considering that AI strategy is multidisciplinary in nature. We therefore provide an agenda to encourage research in various domains related to this important and rapidly expanding topic.

2. How AI differs from earlier digital technologies

Drawing from current literature, we characterize AI as an evolving generation of technologies that collect and interpret data from the environment, generate results, and evaluate the outcomes for autonomous learning, interaction, and problem-solving. AI's applications are diverse, and its potential for recombination has positioned it as a general-purpose technology (i.e., AI can not only be repurposed in multiple industries but also be reused extensively, leading to recognizable spillover effects) (Berente et al., 2021; Raisch & Krakowski, 2021).

AI enables process automation, handles complex games, analyzes structured and unstructured data, generates images, and predicts and mimics human language. Importantly, not only are AI-enabled technologies capable of autonomous learning, but their cognitive tasks, processes, and outcomes are also less scrutable, representing a significant departure from traditional information technologies (e.g., Berente et al. 2021; Krakowski et al., 2023).

[2] Value creation through and with AI is an area of interest in its own right, revolving around both AI itself and its potential for value creation and strategy literature focused on value creation, capture, and even dissemination. These cases are organization-specific and thus beyond the scope of this paper; however, we refer interested readers to Krakowski et al. (2023).

Crucially, AI's ability to learn and act autonomously in decision-making distinguishes it from other digital technologies with limited autonomy (e.g., Berente et al., 2021). While digital technologies shape how and whether—by human or algorithm—processes occur, they happen in concert with human activities. AI, by contrast, iterates autonomously through a "capability to take what [it has] learned and use it to autonomously make decisions, synthesize information, and structure workflows and other processes" (Tang et al., 2022, p. 1022). The rapid advancements in AI have raised concerns about potential risks to society and humanity itself (Future of Life Institute, 2023).

AI is anticipated to have a profound impact on white-collar workers, as it can perform cognitive tasks previously carried out by humans. Unlike previous technologies that primarily automated manual labor (Brynjolfsson & McAfee, 2014), AI has the potential to automate organizational tasks and processes, augment human work, and even replace workers entirely in some industries, altering the nature of work throughout the economy (e.g., Dixon et al., 2021; Raisch & Krakowski, 2021).

AI has changed organizational strategy and value creation rapidly as a result of increasing computational power at lower costs (Moore's law), refined algorithms (e.g., backpropagation, transformers), and the abundance of large-scale data (e.g., from sensors and cell phones). To gain competitive advantages, organizations strive to acquire data and leverage AI, for instance, to better predict customer needs, automate sales processes, and enhance new product development. However, these potentially positive effects of AI hinge on the realization of NEs. In addition, companies must manage the CSP, which inhibits the establishment of NEs. Fig. 1 provides an overview of our conceptual framework.

3. Ai-led value creation explained by data NEs

We build on prior work (e.g., Gregory et al. 2021; Van Alstyne et al., 2016) to explore AI-led value creation from an NEs perspective. This perspective implies that data-driven learning and NEs share a common conceptual framework and give rise to similar economic mechanisms (Clough & Wu, 2022). However, our conceptualization offers several essential distinctions from the original perspective. This elucidation is essential because NEs theory, in its current state, falls short of incorporating the distinct aspects of AI and thus cannot fully explain how users derive value from and contribute value to AI-based systems. While prior research recognizes the critical role of data input for value creation through AI (e.g., Gregory et al., 2021), questions remain about the characteristics of this input. What data sources (e.g., own vs. others' data) provide value to users, and how? Can data value be accurately assessed a priori? Does its value change over time?

Data NEs focus on creating networked value for users, where the utility derived from a platform is determined by the total number of users (Gregory et al., 2021). We consider both organizational and individual users, remaining agnostic about the specific definition of value for these user groups (for a discussion of value creation and subjective value realization by target users, see Lepak et al., 2007). Moreover, we acknowledge that data NEs do not guarantee (or are even the only way) to enable AI-led value creation (for an in-depth discussion, see Knee, 2021). In the following sub-sections, we briefly introduce NEs theory and discuss value creation through this lens. We then carve out the unique aspects of data NEs (i.e., NEs applied to data and AI).

3.1. NEs theory

Literature typically distinguishes between direct NEs and indirect NEs. Through direct NEs, additional actors (typically users adopting new technology) immediately influence the perceived network value to an individual (Eisenmann et al., 2006; Katz & Shapiro, 1985). For example, the more members join a social network, the more opportunities they have to interact with each other, and the greater is the network's value

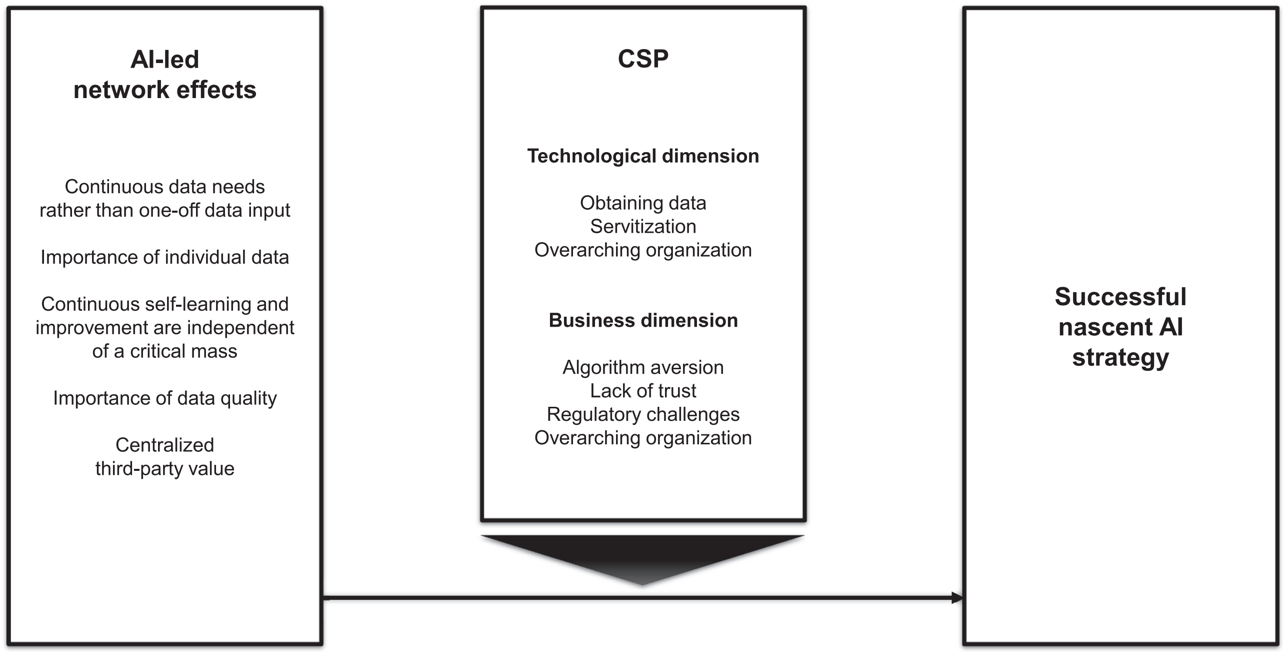

Fig. 1. Conceptual framework.

to each member.

Through indirect NEs, additional users trigger supply-side activities, which then increase the network's value to users (Katz & Shapiro, 1994). For example, in the context of video gaming, a larger installed base of game console adopters induces content producers to increase software supply for the console (e.g., Clements & Ohashi, 2005). The greater availability of games in turn drives demand for the console.

Recent research proposes a third NEs category termed "*data NEs*" (Gregory et al., 2021): the more an algorithm learns from the data it collects, the more valuable the offering becomes to each user, yielding a positive feedback loop. Theoretical debate is ongoing about whether data NEs constitute a unique category and whether established NEs theory still applies in this regard (Clough & Wu, 2022). Furthermore, data NEs may not necessarily result in *positive* feedback loops and could even be subject to opportunistic firm behavior, eventually hurting value creation for users (Clough & Wu, 2022). We build on these arguments and add to the debate by detailing the conceptual underpinnings of data NEs vis-à-vis established NEs, presenting the necessary groundwork for understanding AI-led value creation. We argue that data NEs generally conform to the laws of (indirect) NEs theory but possess unique characteristics, which we explicate next.

3.2. AI-led value creation and NEs theory

The fundamental NEs mechanism relevant to AI is simple: more users of an AI-enabled product or service increase the technology's performance, leading to "superior functionalities of the products…, a more personalized and meaningful experience for each user, or other aspects of … quality" (Gregory et al., 2021, p. 536). Thus, value to a user should generally be a function of network size (Hagiu & Wright, 2021; Katz & Shapiro, 1985), if two conditions are met (Cennamo, 2020; Gregory et al., 2022). Additional data from one user benefits all other users, and benefits arise concurrently, not prospectively. For example, the more visitors interact with a website, the more (and likely more representative) behavioral data they generate, which increases the relevance of, for instance, product recommendations for each visitor, driving further visits in a virtuous cycle.

Arguably, data for training AI may also stem from external sources, decoupling the installed base of users to some degree from AI-led value creation (Clough & Wu, 2022). For example, generative AI can be trained on and learn autonomously from publicly available data sources (e.g., large language models [LLMs]). However, although such models are *pre-trained* on public data, they rely on user interactions to improve further. The use of publicly available data is one way to tackle the CSP, but it only works if the kick-start is sufficient to mobilize further engagement. Moreover, a great deal of data are still private,[3] and such data are often (at least in part) necessary to generate AI-led value for companies: companies need to calibrate consumer recommendation engines to their products, and cross- and up-selling decision support systems require input from companies' existing client base. Other examples are chatbots that access product-specific problem solutions or next-best-action systems that recommend messages and channels to optimize customer communications.

Data NEs are inherently indirect and adhere to the mechanisms proposed in indirect NEs theory. Additional users do not by themselves enhance the technology's value to other users by creating more interaction nodes (in contrast with social networks or communication technology; Katz & Shapiro, 1985); instead, they enable the algorithm, considered a "third party" in NEs terminology, to act on network growth with learning. With an increasing amount of data that is representative and of sufficient quality, the algorithm can create superior value for the technology's users, prompting them to disclose additional data and attracting more users, leading to further improvements and, thus, more value creation.

3.3. Unique dimensions of data NEs

We propose five key dimensions that characterize the unique way algorithms leverage NEs mechanisms to create user value: continuous data needs, importance of individual data, continuous autonomous learning and improvement, input variation in usefulness, and

[3] These private data may be either personal and thus covered by regulations such as the General Data Protection Regulation (GDPR) (EU) 2016/679 (i.e., protection of natural persons with regard to the processing of personal data and on the free movement of such data) or proprietary and thus not openly accessible or legally permissible to use.

Table 1
Unique dimensions of data NEs.

Dimension	Value creation through established indirect NEs	Value creation through data NEs
Continuous data needs	One-off platform adoption	Continuous use for data input
Importance of individual data	Marginal individual contribution and generic complements (e.g., software)	Crucial individual contribution and personalized output
Continuous autonomous learning and improvement	Critical mass as a potential tipping point for economic actors	Autonomous learning as a technical certainty, with the critical mass as a moving target
Input variation in usefulness	Symmetric effects of input (i.e., each adopter has the same marginal impact)	Asymmetric effects of input (i.e., data representativeness, diversity, and timeliness are important)
Centralized third-party value	Many complementary producers responsible for value creation	A few companies responsible for value creation

centralized third-party value. These dimensions not only demonstrate how AI creates value but also shed light on the challenges associated with enabling NEs in the early stages. We draw on these dimensions to further clarify the CSP.

3.3.1. *Continuous data needs*

Unlike the static concept of adoption in indirect NEs theory (Song et al., 2018), data NEs rely on use *intensity*: users' ongoing disclosure of information. AI-led value creation thrives on a continuous information flow to enhance algorithmic predictions. In addition, as the value of data diminishes over time from environmental changes (which is associated with the degradation of algorithm functionality), acquiring new data becomes essential to sustain performance.

3.3.2. *Importance of individual data*

While users stand at the center of indirect NEs, their incremental contribution to the value created through positive feedback loops is negligible. Indirect NEs are inherently a macro-concept; an anonymous volume of adopters drives the value of a platform for an individual user.

In data NEs, the individual user's contribution to prediction quality is far more significant than indirect NEs theory would suggest. Algorithms typically use two types of information to generate individual predictions: aggregate information from other users (i.e., across-user learning; Hagiu & Wright, 2021) and information from the focal user (i.e., within-user learning). Here, individual user behavior directly and noticeably affects the value derived from an algorithm (Gregory et al., 2021). For example, the quality of Netflix's personalized recommendations requires the focal individual's viewing data. Similarly, AI-derived recommendations on improving a salesperson's selling approach largely benefit from that focal employee's data. Prediction quality hinges on the data a particular user contributes, as the algorithm combines what it knows about the individual user with what it knows about other users. Yet the network remains of vital importance; without it, individual predictions are rendered impossible.

3.3.3. *Continuous autonomous learning and improvement*

Indirect NEs theory suggests that a critical mass of adopters is necessary to attract complementary producers (Clements & Ohashi, 2005). Through these producers, the platform gains traction. Thus, their commercial considerations of the attractiveness of a market drive indirect NEs, representing a value-creation *potential*.

By contrast, algorithms steadily enhance prediction accuracy and speed depending on the availability of data points (Gregory et al., 2021), combining data from users to enable and refine their predictions (Cennamo, 2020). A discrete tipping point for third parties to provide value-add does not exist. Thus, market actors' commercial considerations do not influence the beneficial returns to AI-led value creation; rather, ongoing data input and organization-specific learning capabilities are essential.

3.3.4. *Input variation in usefulness*

Established indirect NEs are symmetric in user input because of their macro focus: the characteristics of new network participants are inconsequential, as each new adopter contributes to the "installed base," stimulating the production of complementary goods. However, this principle only partially applies to data NEs. Algorithms rely on data that are of sufficient quality (i.e., adequately representative, diverse, and up to date). Consequently, additional data points can vary in their utility and may even hinder value creation. For example, in automated hiring processes, algorithms lacking a diverse and accurate training database may perpetuate and magnify existing human biases when evaluating employees with diverse backgrounds (e.g., Raisch & Krakowski, 2021).

Relatedly, unreliable data in the form of inauthentic, exceptional, or incomplete input may preclude extrapolation in general and exploratory and inductive insights in particular. Such data may come from users "gaming" the system (Möhlmann et al., 2021) or from competitors' adversarial actions intended to disturb a company's AI-enabled technology. Thus, data quality and composition matter to realize their predictive potential for data NEs.

3.3.5. *Centralized third-party value*

Theory posits that indirect NEs emerge from the participation of multiple companies, referred to as third parties. For example, various complementary producers, such as game publishers, contribute to the economic success of a platform by developing various games for a game console (Wiegand et al., 2023). However, in the context of AI, a small number of large companies, such as Salesforce's "Einstein" customer relationship management system, and specialized start-ups, such as Celonis, dominate algorithm development. While this centralization of AI development can yield high efficiency, it also exposes vulnerabilities to opportunistic organizational behavior (Clough & Wu, 2022). As a case in point, in the context of pricing algorithms, NEs between companies could lead to algorithmic pricing collusion (Hansen et al., 2021). As a result, the realization of positive feedback loops hinges on strategic choices in AI development.

Having identified how data NEs create value (summarized in Table 1), we now link these elements to the CSP. Companies need a "running system" for NEs to unfold (i.e., sufficient data yield accurate predictions and, thus, sufficient user value); however, they likely face a CSP when establishing such a system.

4. Overcoming the AI CSP

Existing research on the CSP for indirect NEs documents two dimensions (Eisenmann et al., 2006): complementors and users. Similarly, we identify two CSP dimensions in the context of AI strategy: a technological and a business dimension (e.g., Gregory et al., 2021). We argue that nascent AI strategy, if it aims to capitalize on data NEs, can only succeed if the company jointly resolves the technological and business dimensions of the CSP by addressing challenges in key underlying dyadic and triadic relationships.

Prior research stresses the significance of data dependencies in data NEs, encompassing factors such as data quality and quantity, the relevance of personal data, transparency in AI predictions, and user engagement with the technology (Gregory et al., 2021). These aspects are integral to our discussion on the CSP. Furthermore, we expand this discourse by incorporating the unique dimensions of data NEs identified in section 3.3. Notably, the two dimensions can intersect. For example, if users, who are part of the business dimension of the CSP, refrain from sharing data, they contribute to challenges on the technological dimension.

We illustrate the relationships in Fig. 2 with quotes from interviews that we conducted with AI strategy experts in finance and information technology (55 interviews, conducted between December 2019 and January 2021). The interviewees possessed a blend of technical and business domain knowledge and were actively involved in AI strategy implementation, both in their organizations and as consultants. While our focus is not on an in-depth examination of these interviews, we reviewed the quotes to establish connections between the challenges the interviewees described and current understanding of data NEs and AI strategy, thus adopting a proof-of-concept approach.

4.1. Technological dimension of the CSP

The technological dimension of the CSP emerges because AI requires both data[4] and appropriate technologies: algorithms that parse (and learn from) data, typically cloud technologies that can store large volumes of data, and the hardware required to run AI-mediated processes (e.g., powerful graphics processing units). These prerequisites come with challenges for a nascent AI strategy design. Moreover, regulations shape (and further restrict) the triadic data–technology–algorithm relationship.

4.1.1. Data–algorithm dyad: data challenges and the CSP

Data are a prerequisite when making predictions and deriving insights. Therefore, data quantity and quality are the core requirements to stimulate data NEs (Gregory et al., 2021), improving AI-enabled technologies' output. AI-enabled algorithms will perform poorly if data quality is low or data are incorrect, an issue that interviewees repeatedly emphasized.

> *One of the big challenges is that we cannot always trust that the data is correct.* (Data scientist, tech consultancy)

Moreover, to unfold data NEs, companies must ensure the continuous use of AI-enabled technology. AI-enabled algorithms need continuous access to up-to-date datasets to adjust predictions and improve performance.

> *To prove that AI works, the client usually wants to have the wow factor. And to show their management that look, we can use … our control datasets…. But to scale it and use AI in your business, you need much more done; you need a plan and structure for getting data.* (Data science manager, tech consultancy)

One solution to guide an algorithm in the absence of data is for a designer to stipulate simple rules (e.g., explicit, logic-based rules) for the algorithm to follow (Shaw et al., 2010), which data-driven and autonomous methods can replace or complement over time. In the absence of representative and diverse data, seemingly less invasive data might be sought: simple categorization by the user (e.g., like/dislike decisions for a short list of outcomes; Zhou et al., 2011) or manual tagging of data (Zhang et al., 2010). Using such tools in organizational settings (e.g., identifying a pre-determined set of recommendations through interviews) might also initiate a virtuous cycle in which additional data can be collected and the algorithm improved upon.

4.1.2. Technology–algorithm dyad: servitization and the CSP

Companies can partially address the technological CSP by purchasing pre-trained, off-the-shelf solutions. For example, many of IBM's "Watson" solutions can be applied without further training or calibration. This strategic decision comes with a classic trade-off: while a more open (but less controlled) approach to innovation tends to accelerate innovation (i.e., AI-led insight), a closed approach (with less innovative potential) allows for more control over both the inputs and the outcomes but limits innovation (Boudreau, 2010).

Another pre-trained solution is LLMs (e.g., GPT-4). Such models typically use available data (e.g., public, online) to train a basic model, which then attracts a user base to mobilize additional data, continuously improving the model. An LLM might thus offer a "head start" for general applications. Yet LLMs come with a limitation, as they are not necessarily suitable for specialized tasks, for which they may need further training based on user data.

Moreover, servitization is an ongoing trend: organizations rely on third-party consultants and service providers for AI strategy development and implementation tailored to different user groups in an organization. For example:

> *We make available an AI workbench … or a framework … for data scientists, data engineers, AI models, to work with, creating … models based on available algorithms and data…. If you're a blackbelt data scientist, that's where you want to be……. But if you want to have a chatbot, you want to train the chatbot on your products and services. Then you won't need [our workbench] because then you would go for one of the off-the-shelf offerings that [company name] and other companies have.* (AI evangelist, tech consultancy)

Organizations thus outsource the development of the algorithm and the choice of the underlying hardware to a third party, and they do so in perpetuity—for example, by purchasing software as a service (SaaS) from organizations such as Amazon (Web Services), Google (Cloud), or Microsoft (Azure). While servitization provides a quick solution to the challenge of insufficient data (part of the CSP), there are long-term consequences. The organization becomes dependent on third parties, not only to propose alterations to core processes but also to help implement them strategically.

4.1.3. Data–technology–algorithm triad: regulatory challenges and the CSP

Finally, regulations set the framework for data and technology usage and thus can contribute to the CSP. Regulation limits which data can be collected, by whom, and under which conditions and thereby can limit the potential of data NEs for AI-led value creation (Gregory et al., 2021).

Examples include data privacy regulations such as the GDPR or the California Consumer Privacy Act. A particular focus has been on the collection and usage of personal data, including IP addresses or cookie identifiers, from users such as customers and employees. Typically, organizations are only allowed to process such data after receiving users' explicit consent and should collect data only for specified and limited purposes (i.e., data minimization) (e.g., Skiera et al., 2022).

The data minimization principle further contributes to the CSP. Organizations are legally obliged to limit data collection to that which they effectively need. However, data minimization contradicts the oftentimes exploratory nature of AI-enabled algorithms and limits data variety that is beneficial to spurring data NEs. Algorithms often give better predictions than theoretical expectations because they identify and test patterns on the basis of data interactions rather than building a model to understand how and why things occur (Leavitt et al. 2021). This exploratory and *ex post* process renders it almost impossible to predict which data are necessary. An interviewee describes these tensions:

[4] We predominantly focus on primary user data, that is, data that users actively or implicitly share with a company. However, we acknowledge that companies can also leverage secondary data sources (e.g., general market developments, user posts in open social networks).

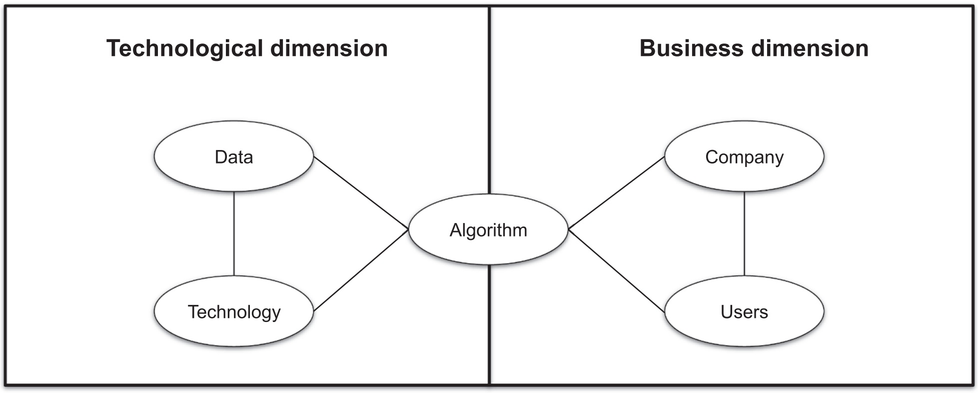

Fig. 2. The CSP's technological and business dimensions.

> [With] GDPR, you have … data minimization: you should only use what is needed. But when we also know that we need a lot of data to ensure that our applications or algorithms are working well … that's sort of a contradiction. (AI strategist, bank)

Moreover, regulations, including GDPR, but also those likely to be covered in more depth in the proposed AI Act currently under consideration by the European Parliament (2023), require that organizations disclose how they process data and provide an explanation on how their AI-enabled algorithms reach a conclusion. However, AI-enabled algorithms likely offer only "black-box" solutions, as they are typically multilayered, complex, and opaque in how they arrived at a conclusion. Consequently, these regulations contribute further to the CSP by reducing the range of applicable algorithms and, thus, limiting the potential to leverage data NEs (Gregory et al., 2021).

4.2. Business dimension of the CSP

In addition to the technological dimension, the CSP's business dimension has become increasingly important (Fig. 2). Challenges in the dyadic relationships between the algorithm and users (here, customers and employees), as well as the company, have an impact on the CSP. Moreover, the CSP likely depends on which motivations users infer from the company's AI usage (triadic users–company–algorithm relationship).

4.2.1. User–algorithm dyad as a source of the CSP

User engagement is typically important for data NEs to unfold (Gregory et al., 2021). However, various perspectives, such as the technology acceptance model, appraisal theory, and ethical decision-making theory, provide insights into user hesitance to adopt AI-enabled technologies (for a comprehensive overview, see Habel et al., 2023). In this sub-section, we discuss the role of algorithm aversion and privacy concerns, as they may cause users to disregard recommendations and withhold data from the algorithm, restricting data NEs and fueling the CSP.

First, algorithm aversion refers to humans' tendency to disproportionately rely on their own judgment or on input from other human agents over that of algorithmic agents when making decisions (Burton et al., 2020; Dietvorst et al., 2015). Consequently, users may disregard demonstrably valuable algorithmic recommendations, reducing the potential for AI-enabled machines to learn and improve over time. Algorithm aversion can occur in various contexts, including sales. For example, chatbots closed as many sales as human call center agents when customers were unaware that they were interacting with a chatbot. However, sales dropped by approximately 80% when the organization disclosed that a chatbot made the call (Luo et al., 2021).

Aversion may stem from a confirmation bias, in which users, having experienced a mistake made by an algorithm, believe that all algorithms err (Dietvorst et al., 2015). However, studies have also identified aversion even if no algorithmic error occurs (for an overview, see Chugunova & Sele, 2022). Moreover, the extent of algorithm aversion is context-dependent. For example, aversion is more likely to occur in hedonic contexts (Longoni & Cian, 2022) and when users are less able to understand and affect algorithmic functioning or behavior (Uysal et al., 2022). Finally, aversion may result from the opaque nature of algorithmic recommendations. Algorithms are typically not transparent in how they arrive at a given output, making users less accepting of such opaque recommendations (Kellogg et al., 2020).

Managers can decrease algorithm aversion by allowing users to make (even only minor) adjustments to the algorithm (Dietvorst et al., 2018). Aversion also decreases when humans communicate advice from an AI tool instead of the AI tool directly communicating the advice (Longoni & Cian, 2022). As algorithm aversion likely arises when the algorithm (partly) replaces the decision-maker (Chugunova & Sele, 2022), augmenting human decision-makers with AI instead of (partly) replacing them could pre-empt algorithm aversion (Raisch & Krakowski, 2021).

Second, users may refrain from sharing data or provide inaccurate information out of privacy concerns. When users perceive organizations as excessively collecting data, they may feel a loss of control and ownership over their data, leading to negative affect and behavioral reactance (Puntoni et al., 2021). Consequently, users become less willing to share their data.

Research shows that humans follow a privacy calculus to determine whether to share their data, trading off the associated risks and benefits (e.g., Beke et al., 2022). For example, drivers need to share data on their driving behaviors for usage-based car insurance and thereby risk third parties intercepting their location information for malicious use.

Managers need to be aware of these privacy concerns and help reduce them, for example, by collecting less sensitive data (Beke et al., 2022). Thus, they need to engage in a trade-off between data quality (as sensitive data might be valuable for data NEs) and data access (as users may not provide any data if they have privacy concerns). Additional measures for companies to decrease privacy concerns include granting users increased control over their data, being more transparent about data collection and usage, and working to enhance trust (Bleier et al., 2020).

4.2.2. Company–algorithm dyad as a source of the CSP

Regarding the challenges of AI adoption within organizational contexts (e.g., Agrawal et al., 2022), companies' formal (e.g., structures) and informal (e.g., culture) elements can contribute to the CSP. First, a company's formal elements can lower data NEs and thus provoke the CSP. For example, misalignment between incentive systems (e.g., employees' sales-based variable compensation) and AI-enabled recommendations (e.g., maximizing profits) can cause employees to reject AI technology (Vomberg, 2021). Thus, managers need to align AI-enabled technology with their human resource management approach (e.g., Raisch & Krakowski, 2021) for data NEs to materialize.

Moreover, a company's organizational structure can lead to the CSP (Agrawal et al., 2022). To promote data NEs, AI must have access to various data sources. However, established company structures are widely associated with data silos: data remain in functional areas instead of being shared. Thus, companies frequently struggle to integrate data across sales channels (The CMO Survey, 2022) and particularly between distinct functional domains, reducing the potential to leverage data NEs.

To overcome the CSP, organizations typically need to redefine established workflows. This is to ensure that AI-enabled technology can not only unfold its unique potential but also be optimally integrated into human tasks, augmenting human skills and thus allowing for continued adoption and usage. Such an approach requires the separation of prediction (in which AI-enabled technology is beneficial) and decision-making (in which human judgment is helpful) in workflows (Agrawal et al., 2018) adopting appropriate human–AI decision-making structures depending on contextual requirements (Shrestha et al., 2019). However, such changes may require company-wide transformations (Agrawal et al., 2022), likely redefining departmental boundaries, as a tech consultant elaborated:

> *If you look at the back-office functions … I think you have to know that you will always need to remove boundaries with the help of technology, but you also risk creating new obstacles and boundaries.* (Data science manager, tech consultancy)

Second, regarding informal elements, the prevailing mindset in many organizations is not ideally conducive to successful adoption of AI, thereby contributing to the CSP. Historically, many companies followed a zero-defects paradigm (i.e., error-free processes). However, AI-based predictions likely improve over time and benefit from ongoing experimentation to stimulate data NEs. Thus, AI-enabled technologies require a trial-and-error mentality and failure tolerance (e.g., Tang et al., 2022). One bank employee emphasized:

> *We come up with different solutions and introduce those to the management, execute management, and then luckily, they support us. So we could share the facts and communicate what could be done, perhaps could be done, and we can have an opportunity to try it out.* (AI strategist, bank)

Without a mindset open to perceived failures, employees may be discouraged from relying on AI predictions. Organizations can nurture such open cultures through symbolic acts, such as the "heroic failure award" reportedly humorously handed out by Procter & Gamble (Vomberg et al., 2020).

4.2.3. *User–company–algorithm triad as a source of the CSP*

In addition to dyadic relationships, the user–company–algorithm triad can be a source of the CSP. Whether users will share data with AI-enabled machines may ultimately depend on what motives they infer from the system's use at a more general level (e.g., Venkatesh, 2022). Scant research has thus far evaluated this aspect in the context of AI.

First, employees may fear replacement by technology, referred to as "automation anxiety" (Autor, 2015). For example, "real estate services such as OJO Labs, REX Real Estate, and Roof.ai have replaced human real estate agents with chatbots empowered by AI" (Longoni & Cian, 2022, p. 91). Perceived AI-related replacement threats are common in various occupations (Dixon et al., 2021). As such tools can act and learn without human intervention, they can at least partly replace tasks of which humans had conventionally been in charge (e.g., Luo et al., 2021). Moreover, across-user learning (which characterizes data NEs) may enable employees to replace their co-workers or managers (Dixon et al, 2021). For example, salespeople who share their customer knowledge with AI-enabled customer relationship management systems may risk their co-workers pilfering their customers (Vomberg et al., 2023). One interviewee elaborated:

> *A lot of people focus on cost-cutting. And of course, it's always appealing to companies to try and do more with less, or the same with less, and people costs are, of course, the big chunk of many companies' business.* (AI evangelist, tech consultancy)

Customers may also respond negatively to AI-enabled technology if they infer that companies installed the technology for cost-cutting—for example, to replace employees (Castelo et al., 2023). Similarly, Uysal et al. (2022) found that consumers perceive AI technology as competing with and replacing human intelligence, reducing their data-sharing willingness.

Second, the adoption of AI technology also raises concerns about surveillance. For example, Uber drivers have reported that Uber's algorithmic management undermines their sovereignty (Möhlmann et al., 2021), and salespeople believe that managers use AI-based technologies to control their daily business activities (Habel et al., 2023). Such concerns can lead to so-called algo-activism, in which users game AI-enabled systems by using them in unintended ways or even manipulating the data (Kellogg et al., 2020; Vomberg et al, 2023); thus, they decrease the value of data NEs and amplify the CSP.

Thus far, research on overcoming the CSP from the user–company–algorithm triad is sparse. One possible solution is a stepwise rollout of AI solutions and the joint evaluation of the technology's effectiveness together with its users (Vomberg, 2021). Thus, we align with other calls for future research to explore this triad (see Kellogg et al., 2020).

5. Research agenda

We contribute to the understanding of data NEs and the CSP as a pervasive hurdle in nascent AI strategy. We find that overcoming the CSP is a necessary, but not sufficient, part of successful AI strategy implementation—and ultimately of AI-led value creation. Building on literature from multiple disciplines, we outline five unique dimensions of data NEs. These dimensions help explain how AI technologies create value and identify focal challenges contributing to the CSP. Specifically, we discuss the technological and business dimensions of the CSP and how they intersect to shape and constrain value creation through data NEs.

Data NEs is a burgeoning field of research, and empirical studies of AI-led value creation are sparse. Accordingly, we proceed to offer suggestions for future research. We relate these suggestions to specific aspects of the CSP inherent in data NEs, tying them back to our previously identified strategies for mitigating and managing the challenges (see Table 2).

First, regarding the CSP's technology dimension, more research on the *data–algorithm dyad* is required. Researchers should explore how organizations can obtain sufficient starting data in quantity and quality. This includes research into new and improved ways of generating data (e.g., synthetic data) to later update them and new ways to meaningfully integrate existing and multimodal data from other fields or applications. Additional relevant questions include the following: how can organizations better engage employees to, for instance, create sufficient starting points? How can companies detect fraudulent and adversarial data?

Second, we call for further research on the *technology–algorithm dyad*. For example, how can companies get access to technology and use servitization? How can organizations move from pre-trained applications to in-house understanding and development of AI-enabled algorithms? In what situations can servitization be a viable long-term choice, and how should the relationship with the external party be shaped? Moreover, how should organizations be organized to allow for the development of in-house skills and knowledge to code and manage the algorithms themselves?

Third, future research should examine the *data–technology–algorithm triad* by exploring how regulatory challenges shape the technology-data

Table 2
Opportunities for future research.

CSP dimension	Related NEs dimensions	Identified strategies	Example research questions
Technological dimension			
Data–algorithm dyad	Continuous data needs Input variation in usefulness Continuous autonomous learning and improvement	Start with simple rules Data-light approach LLMs	How can companies generate better synthetic starting data? How can companies protect and distinguish proprietary data from public data? How can companies better integrate existing data from other applications? How can companies better engage employees in creating meaningful starting points? How can companies detect adversarial data?
Technology–algorithm dyad	Importance of individual data Centralized third-party value	Purchase of pre-trained solutions Quasi-solution: servitization	How can companies navigate make-or-buy decisions? How can companies move from pre-trained applications to in-house development of AI applications? When is servitization a viable long-term choice? How can companies optimally shape the relationship with external providers? How can companies attract and recruit AI talent? Which skill sets are required at different organizational levels (i.e., upskilling)? How can companies organize to develop in-house skills and knowledge?
Data–technology–algorithm triad	Continuous data needs Importance of individual data Input variation in usefulness Centralized third-party value	–	What new algorithms and techniques can be developed to maximize insights from minimal data? What algorithms and techniques can be developed that help mitigate AI opacity? How can companies motivate users to provide informed consent for their data usage? How can companies govern employees' use of external AI applications?
Business dimension			
User–algorithm dyad	Continuous data needs Importance of individual data Input variation in usefulness Continuous autonomous learning and improvement	Allow adjustments to the algorithm Rely on humans to communicate AI output Collect sensitive data only if necessary	How can companies adjust structure and actions to overcome the perceived loss of control? Which actions can help overcome algorithm aversion? What factors trigger algorithm aversion vs. algorithm appreciation? How can explainable AI stimulate users' trust in AI?
Company–algorithm dyad	Continuous data needs Importance of individual data	Separate forming predictions and decision-making Redefine departmental boundaries Promote trial-and-error learning	How important is task-level vs. company-level adoption? How can companies stimulate an appropriate culture and mindset related to AI adoption? How can companies be structured for employees to leverage AI as a tool for augmentation? How can companies stimulate collaboration between AI and employees? How can companies manage the transition period after the AI adoption?
User–company–algorithm triad	Continuous data needs Importance of individual data Input variation in usefulness Continuous autonomous learning and improvement	Stepwise rollout of AI technology	How can managers successfully communicate AI adoption? How can managers overcome suspicions of an AI adoption? How can companies organize to best counter users gaming the system? Which novel jobs can and should emerge? Which role do leadership styles play when adopting AI? How relevant are threats from AI compared to opportunities? Which regulatory frameworks ensure a safe and ethical implementation of AI systems?

interrelationships. New AI-enabled algorithms and techniques (e.g., federated learning, edge computing) that meet anonymization and minimization principles should be developed and applied to maximize insights from minimal data collection. Such algorithms should also offer maximum insight and understanding, moving AI away from the current black-box status-quo characterized by opaque and inscrutable algorithms. Moreover, which strategies can companies develop to acquire informed consent from users to leverage their data? In addition to external regulations, which internal governance mechanisms are necessary? For example, which internal regulations can help prevent other users or organizations from accessing secret or sensitive company data if employees use external AI technology (e.g., LLMs).

Fourth, regarding the CSP's business dimension, we call for further research on the *user–algorithm dyad*. Psychology-based research should tackle the perceived loss of control when companies rely on user data. Furthermore, scholars should explore which actions managers can take to mindfully overcome algorithm aversion. Relatedly, future research should examine which conditions and reasons spur algorithm aversion and which factors foster the opposite outcome (algorithm appreciation, or the tendency to prefer algorithmic to human advice; Burton et al., 2020), along with contextual and behavioral factors that determine appropriate reliance on the two types of advice. In addition, future research should evaluate the degree of explainable AI necessary to overcome user resistance. Do users require in-depth understanding of how AI reached a focal conclusion? Or do general insights into how an AI-enabled algorithm performs and which goals it aims to achieve suffice?

Fifth, researchers should further explore the *company–algorithm dyad*. How should companies integrate AI-led value creation at the task or company level. At the task level, managers rely on AI-enabled technology to enhance the precision of decisions that employees currently make (e.g., automating the prediction of customer churn). At the company level, managers may restructure decision processes to fully benefit from AI-enabled predictions (e.g., moving toward algorithmic management) (e.g., Agrawal et al. 2022) or design processes that strike a balance through various hybrid and sequential approaches (Shrestha et al., 2019). Moreover, research is necessary to understand how companies can adjust their formal and informal elements to benefit from AI-led value creation. How do company cultures become open to AI? How can managers make employees see AI as an ally and foster collaboration with it (with AI as a team member or manager)? As change processes need time to unfold, future research should also explore how companies should manage the transition period until returns from data NEs materialize (e.g., identification of milestones).

Sixth, we call for future research on the *user–company–algorithm triad*. Scholars should explore how managers can communicate AI-enabled technology adoption. Users may perceive AI adoption more favorably if managers emphasize responding to competitive pressures or frame the adoption as an augmentation opportunity for employees to reskill, upskill, and take on new, more rewarding roles with higher added value for themselves as well as the company (Daugherty & Wilson, 2018; Raisch & Krakowski, 2021). Moreover, while employees may fear replacement, AI-enabled machines may also create novel job opportunities (Dixon et al., 2021), which research should explore. Future research should also explore how organizations can prevent users from gaming the system and which leadership styles are effective in adopting AI-led technology. In addition, studies on how serious perceived threats (e.g., threats of replacement and surveillance) are relative to the potential benefits of AI-enabled technology are warranted. Last, as advancements in AI capability seem to evolve at a much faster pace than understanding of exact model functioning, research should investigate regulatory frameworks to ensure safe and ethical implementation of AI systems.

6. Conclusion

We argue that the success of nascent AI-led strategies crucially hinges on data NEs and that these differ qualitatively from established conceptualizations of NEs in important ways. As data NEs are subject to the CSP, we also show how the CSP's technological and business dimensions can jointly prevent the realization of virtuous cycles associated with data NEs. We hope that our discussion and research agenda spark further work on ways to overcome the CSP and to allow for the emergence of data NEs, which in turn will enable organizations to move from a nascent AI strategy to AI-led value creation.

CRediT authorship contribution statement

Arnd Vomberg: Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Nico Schauerte:** Writing – review & editing, Writing – original draft, Conceptualization. **Sebastian Krakowski:** Writing – review & editing, Writing – original draft, Data curation, Conceptualization. **Claire Ingram Bogusz:** Writing – review & editing, Writing – original draft, Data curation, Conceptualization. **Maarten J. Gijsenberg:** Writing – review & editing, Writing – original draft, Conceptualization. **Alexander Bleier:** Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Acemoglu, D., Anderson, G., Beede, D., Buffington, C., Childress, E., Dinlersoz, E., Foster, L., Goldschlag, N., Haltiwanger, J., Kroff, Z., Restrepo, P., & Zolas, N. (2022). Automation and the workforce: A firm-level view from the 2019 annual business survey. NBER working paper.

Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: The simple economics of artificial intelligence*. Harvard Business Press.

Agrawal, A., Gans, J., & Goldfarb, A. (2022). *Power and prediction: The disruptive economics of artificial intelligence*. Harvard Business School Press.

Autor, D. H. (2015). The paradox of abundance: Automation anxiety returns. In S. Rangan (Ed.), *Performance and progress: Essays on capitalism, business and society*. Oxford University Press.

Beke, F. T., Eggers, F., Verhoef, P. C., & Wieringa, J. E. (2022). Consumers' privacy calculus: The PRICAL index development and validation. *International Journal of Research in Marketing, 39*(1), 20–41.

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly, 45*(3), 1433–1450.

Bleier, A., Goldfarb, A., & Tucker, C. (2020). Consumer privacy and the future of data-based innovation and marketing. *International Journal of Research in Marketing, 37* (3), 466–480.

Boudreau, K. (2010). Open platform strategies and innovation: Granting access vs. devolving control. *Management Science, 56*(10), 1849–1872.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W.W: Norton.

Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). *Notes from the AI frontier: Modeling the impact of AI on the world economy*. McKinsey & Company. Discussion paper,.

Burton, J. W., Stein, M. K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making, 33*(2), 220–239.

Castelo, N., Boegershausen, J., Hildebrand, C., & Henkel, A. P. (2023). Understanding and improving consumer reactions to service bots. *Journal of Consumer Research*. https://doi.org/10.1093/jcr/ucad023

Cennamo, C. (2020). *Value preserving platform regulation: Network effects, platform value, and regulatory remedies*. Copenhagen Business School. Working paper,.

Chugunova, M., & Sele, D. (2022). An interdisciplinary review of the experimental evidence on how humans interact with machines. *Journal of Behavioral and Experimental Economics, 99*, Article 101897.

Clements, M. T., & Ohashi, H. (2005). Indirect network effects and the product cycle: Video games in the US, 1994–2002. *Journal of Industrial Economics, 53*(4), 515–542.

Clough, D. R., & Wu, A. (2022). Artificial intelligence, data-driven learning, and the decentralized structure of platform ecosystems. *Academy of Management Review, 47* (1), 184–189.

CMO Survey, The (2022, February). The CMO survey: Highlights and insights report. https://cmosurvey.org/wp-content/uploads/2022/02/The_CMO_Survey-Highlights_and_Insights_Report-February_2022.pdf.

Csaszar, F. A., & Steinberger, T. (2022). Organizations as artificial intelligences: The use of artificial intelligence analogies in organization theory. *Academy of Management Annals, 16*(1), 1–37.

Dastin, J. (2018, October 10). Amazon scraps secret AI recruiting tool that showed bias against women, Reuters. https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G.

Daugherty, P. R., & Wilson, H. J. (2018). *Human + machine: Reimagining work in the age of AI*. Harvard Business Press.

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.

Dixon, J., Hong, B., & Wu, L. (2021). The robot revolution: Managerial and employment consequences for firms. *Management Science, 67*(9), 5586–5605.

Eisenmann, T., Parker, G., & Van Alstyne, M. (2006). Strategies for two-sided markets. *Harvard Business Review, 84*(10), 92-101, 149.

European Parliament (2023). AI Act: A step closer to the first rules on artificial intelligence. https://www.europarl.europa.eu/news/en/press-room/20230505IPR84904/ai-act-a-step-closer-to-the-first-rules-on-artificial-intelligence.

Future of Life Institute (2023, March 22). Pause giant AI experiments: An open letter. https://futureoflife.org/open-letter/pause-giant-ai-experiments/.

Gregory, R. W., Henfridsson, O., Kaganer, E., & Kyriakou, H. (2021). The role of artificial intelligence and data network effects for creating user value. *Academy of Management Review, 46*(3), 534–551.

Gregory, R. W., Henfridsson, O., Kaganer, E., & Kyriakou, H. (2022). Data network effects: Key conditions, shared data, and the data value duality. *Academy of Management Review, 47*(1), 189–192.

Grisot, M., Hanseth, O., & Thorseng, A. A. (2014). Innovation of, in, on infrastructures: Articulating the role of architecture in information infrastructure evolution. *Journal of the Association for Information Systems, 15*(4), 197–219.
Habel, J., Alavi, S., & Heinitz, N. (2023). A theory of predictive sales analytics adoption. *AMS Review*. https://doi.org/10.1007/s13162-022-00252-0
Haftor, D. M., Climent, R. C., & Lundström, J. E. (2021). How machine learning activates data network effects in business models: Theory advancement through an industrial case of promoting ecological sustainability. *Journal of Business Research, 131*, 196–205.
Hagiu, A., & Wright, J. (2020). When data creates competitive advantage. *Harvard Business Review, 98*(1), 94–101.
Hagiu, A., & Wright, J. (2021). Data-enabled learning, network effects, and competitive advantage. *Working paper*. Boston University.
Hansen, K. T., Misra, K., & Pai, M. M. (2021). Frontiers: Algorithmic collusion: Supra-competitive prices via independent algorithms. *Marketing Science, 40*(1), 1–12.
Heaven, W. D. (2021). Hundreds of AI tools have been built to catch covid. None of them helped. *MIT Technology Review*, https://www.technologyreview.com/2021/07/30/1030329/machine-learning-ai-failed-covid-hospital-diagnosis-pandemic/.
Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *American Economic Review, 75*(3), 424–440.
Katz, M. L., & Shapiro, C. (1994). Systems competition and network effects. *Journal of Economic Perspectives, 8*(2), 93–115.
Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*, 366–410. https://doi.org/10.5465/annals.2018.0174
Knee, J. A. (2021). *The platform delusion: Who wins and who loses in the age of tech titans*. Penguin.
Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal, 44*(6), 1425–1452.
Lam, X. N., Vu, T., Le, T. D., & Duong, A. D. (2008, January). Addressing cold-start problem in recommendation systems. In W. Kim & H. J. Choi (Eds.), *Proceedings of the 2nd international conference on Ubiquitous information management and communication* (pp. 208-211). Association for Computing Machinery.
Leavitt, K., Schabram, K., Hariharan, P., & Barnes, C. M. (2021). Ghost in the machine: On organizational theory in the age of machine learning. *Academy of Management Review, 46*(4), 750–777.
Lepak, D. P., Smith, K. G., & Taylor, M. S. (2007). Value creation and value capture: A multilevel perspective. *Academy of Management Review, 32*(1), 180–194.
Longoni, C., & Cian, L. (2022). Artificial intelligence in utilitarian vs. hedonic contexts: The "word-of-machine" effect. *Journal of Marketing, 86*(1), 91–108.
Luo, X., Qin, M. S., Fang, Z., & Qu, Z. (2021). Artificial intelligence coaches for sales agents: Caveats and solutions. *Journal of Marketing, 85*(2), 14–32.
Möhlmann, M., Zalmanson, L., Henfridsson, O., & Gregory, R. W. (2021). Algorithmic management of work on online labor platforms: When matching meets control. *MIS Quarterly, 45*(4), 1999–2022.
Murry, A. (2017, June 8). *Fortune 500 CEOs see AI as a big challenge*. https://fortune.com/2017/06/08/fortune-500-ceos-survey-ai/.
Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of Marketing, 85*(1), 131–151.
Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210.
Ransbotham, S., Kiron, D., Candelon, F., Khodabandeh, S., Chu, M., & Lafountain, B. (2022). AI empowers employees, not just companies, BCG Global. https://www.bcg.com/publications/2022/the-value-of-ai-for-individuals (Accessed: 18 May 2023).
Shaw, G., Xu, Y., & Geva, S. (2010). Using association rules to solve the cold-start problem in recommender systems. In M. J. Zaki, J. X. Yu, B. Ravindran, & V. Pudi (Eds.), *Pacific-Asia conference on knowledge discovery and data mining* (pp. 340–347). Springer.
Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review, 61*(4), 66–83.
Skiera, B., Miller, K., Jin, Y., Kraft, L., Laub, R., & Schmitt, J. (2022). The impact of the General Data Protection Regulation (GDPR) on the online advertising market. *Amazon eBook*.
Song, P., Xue, L., Rai, A., & Zhang, C. (2018). The ecosystem of software platform: A study of asymmetric cross-side network effects and platform governance. *MIS Quarterly, 42*(1), 121–142.
Tang, P. M., Koopman, J., McClean, S. T., Zhang, J. H., Li, C. H., De Cremer, D., … Ng, C. T. S. (2022). When conscientious employees meet intelligent machines: An integrative approach inspired by complementarity theory and role theory. *Academy of Management Journal, 65*(3), 1019–1054.
Uysal, E., Alavi, S., & Bezençon, V. (2022). Trojan horse or useful helper? A relationship perspective on artificial intelligence assistants with humanlike features. *Journal of the Academy of Marketing Science, 50*, 1153–1175.
Van Alstyne, M. W., Parker, G. G., & Choudary, S. P. (2016). Pipelines, platforms, and the new rules of strategy. *Harvard Business Review, 94*(4), 54–62.
Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research, 308*(1), 641–652.
Vomberg, A. (2021). Pricing in the digital age: A roadmap to becoming a dynamic pricing retailer. In T. Bijmolt, T. Broekhuizen, B. Baalmans, & N. Fabian (Eds.), *The digital transformation handbook–From academic research to practical insights* (pp. 1–21). University of Groningen Press.
Vomberg, A., Alavi, S., & Oproiescu, A. L. (2023). Driving CRM tech success: Contingent effects of algorithm-based CRM technology implementation on profitability. *Working paper*. University of Mannheim.
Vomberg, A., Homburg, C., & Gwinner, O. (2020). Tolerating and managing failure: An organizational perspective on customer reacquisition management. *Journal of Marketing, 84*(5), 117–136.
Wiegand, N., Peers, Y., & Bleier, A. (2023). Software multihoming to distal markets: Evidence of cannibalization and complementarity in the video game console industry. *Journal of the Academy of Marketing Science, 51*, 393–417.
Zhang, Z. K., Liu, C., Zhang, Y. C., & Zhou, T. (2010). Solving the cold-start problem in recommender systems with social tags. *EPL (Europhysics Letters), 92*(2), 28002.
Zhou, K., Yang, S. H., & Zha, H. (2011). Functional matrix factorizations for cold-start recommendation. In W.-Y. Ma & J.-Y. Nie (Eds.), *Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval* (pp. 315-324). Association for Computing Machinery.

Arnd Vomberg is Professor of Digital Marketing & Marketing Transformation at the University of Mannheim, Germany.

His research focuses on key challenges which marketing and sales managers face in the fields of ongoing digital transformation, agility transformation, and the shift to a socially responsible marketing approach.

His work has been published in the Journal of Marketing, the Journal of Marketing Research, the Strategic Management Journal, the Journal of the Academy of Marketing Science, and the International Journal of Research in Marketing, among others.

Nico Schauerte is Associate Professor of Technology & Innovation Marketing at the Vrije Universiteit Amsterdam, the Netherlands.

His research mainly focusses on topics related to technology and innovation marketing. His work on digital platforms includes the dynamics of hardware-software and software-software systems, such as entertainment systems or automobiles, but also matchmaking and brand platforms like branded apps.

His work has been published in the Journal of Marketing, the Journal of the Academy of Marketing Science, the International Journal of Research in Marketing, the Journal of Interactive Marketing, and the Harvard Business Review, among others

Sebastian Krakowski is Assistant Professor at the Stockholm School of Economics, Sweden.

His research interests include digital transformation, organizational behavior, and strategy. Specifically, he explores how digital technologies like artificial intelligence impact organizational theory and applied strategy. His research analyzes how organizations create value through the adoption and development of digital technology, with a particular focus on the interaction between human beings and algorithms. He also explores societal and ethical aspects of digitalization.

His work has been published in the Academy of Management Review and the Strategic Management Journal, among others.

Claire Ingram-Bogusz is Associate Professor of Information Systems at Uppsala University, Sweden and Affiliated Researcher at the House of Innovation, Stockholm School of Economics, Sweden.

Her research investigates how code-based technologies (e.g. code itself, digital platforms, machine learning, digital automation) are changing how we work, how organizing occurs, and what these things mean for us as individuals and as members of increasingly unequal societies.

Her work has been published in the Journal of the Association of Information Systems, the Information Systems Journal, the IEEE Transactions on Engineering Management, and the Academy of Management Proceedings, among others. Besides, she has written numerous book chapters on her research topics.

Maarten J. Gijsenberg is Professor of Marketing Dynamics at the University of Groningen, the Netherlands.

His research mainly focusses on the econometric modelling of marketing decisions (timing and size of investments, targeting of actions) and their effectiveness, with special attention to the over-time dynamics of the latter (due to e.g. the impact of both macro-economic and firm-specific crises on consumers' behavior), and main focus on advertising.

His work has been published in the Journal of Marketing Research, the International Journal of Research in Marketing, the Journal of Business Research, and Frontiers in Psychology, among others.

Alexander Bleier is Associate Professor of Marketing at the Frankfurt School of Finance & Management, Germany.

His primary research interests lie at the intersection of digital marketing, customer relationship management, and consumer decision making. A particular focus concerns the investigation of marketing communication and personalization strategies.

His work has appeared in Marketing Science, the Journal of Marketing, theJournal of Consumer Research, the Journal of the Academy of Marketing Science, the International Journal of Research in Marketing, and the Harvard Business Review, among others.