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Reinventing Innovation Management: The Impact of Self-Innovating Artificial Intelligence

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Abstract:
Through recent leaps in application, artificial intelligence (AI) has become one of the most promising digital technologies, attracting significant attention from scholars and practitioners alike. Prior innovation research has mainly focused on the opportunities for and challenges to infusing digital technologies into the innovation process. However, understanding the general effects of digital technologies is insufficient as their specific fields of application differ. AI is distinct from other digital technologies, given its potential to evolve into both a general-purpose technology and a method of inventing, and several firms are beginning to integrate AI into their innovation processes. We capture this phenomenon by introducing a concept we term self-innovating artificial intelligence (SAI), defined as the organizational utilization of AI with the aim of incrementally advancing existing or developing new products, based on insights from continuously combining and analyzing multiple data sources. As SAI is about to fundamentally change how innovations are created, this article describes the underlying AI technology; conceptualizes and outlines how firms may incorporate SAI into their innovation processes with the aim of developing increasingly complex products; and offers potential avenues for further research in this intriguing domain.

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SECTION I.
Introduction

Today's products and services increasingly rely on artificial intelligence (AI) as a source of innovation [1], [2], such as Apple's virtual assistant Siri [3], skin-cancer detection systems [4], automatized accounting and auditing processes [5], and service robots [6]. However, as the application fields of AI rapidly increase, several firms are advancing beyond simply embedding AI into products and services by incorporating AI into their innovation processes, so as to incrementally enhance existing and develop new products [7]. For instance, Berg (a Massachusetts-based biopharma company) recently introduced an AI platform which analyzes patient biology and is able to discover differences between healthy and cancerous cells. Berg's AI platform revealed naturally occurring patterns of molecules in cancer metabolism, and ultimately paved the way for developing BPM31510, a drug currently being tested on people with advanced pancreatic cancer [8].

Despite rapid advances, AI remains in a fledgling stage, with applications currently limited to somewhat narrow fields (such as Berg's drug discovery). However, most scholars and practitioners concur that there is far more to come [9]– [12], and even predict an AI-driven fourth industrial revolution [13]. Boundaries between AI agents and humans are set to diminish, and, instead, AI agents both acting autonomously and collaborating with humans are expected to generate radically new explanations and inventions [9]. Such advances in application suggest that AI can be characterized as an “invention of a method of inventing” [14, p. 502], as well as having the potential to evolve into a general-purpose technology [15], [16], i.e., being able to innovate autonomously across a great range of products, thereby disrupting entire innovation processes and fundamentally changing how innovations are created [17].

Surprisingly, and despite continuously increasing practical applications of AI within organizations, innovation literature has mostly overlooked these recent advances, instead focusing primarily on the broad topic of digitization [18]– [21] and, more specifically, on the merits of big data (e.g., [22]– [29]) and three-dimensional (3-D) printing (e.g., [30], [31]). However, it is essential to fully understand each separate component of the ongoing digitization in order to fully understand the big digitization picture. Nambisan [19, p. 1030] rightly states that “explicitly theorizing about digital technologies and their characteristics” enables the scholarly innovation community to keep pace with the rapidly advancing digitization of innovation processes. With AI being a major driver of digitization distinct from other digital technologies, it is crucial to re-evaluate and retheorize the innovation process considering recent advances and future prospects in AI.

For this purpose, it is essential to take a more technical and contextualized approach to the AI technology. Computer scientists have always been at the forefront of observing and fostering the digitization of organizational processes [18]. Especially in the field of AI, most advances and academic publications originate from computer scientists [32]. Increasingly, computer scientists are also dealing with the digitization of innovation processes [21], [33]– [38]. These rapid advances through computer scientists regarding AI increasingly challenge the fundamental assumptions of established innovation theories. Traditional innovation theories are characterized by presuming highly bounded innovation processes, centralized innovation agency, and strict boundaries between innovation processes and innovation outcomes [18]. However, recent advances in AI achieved through computer scientists increasingly challenge these fundamental premises, which necessitate novel contextualized theorizing on how AI and its individual characteristics influence innovation.

This article perspective aims to address this gap in the literature by introducing the concept of “self-innovating artificial intelligence” (SAI) to describe how firms incorporate AI into their innovation processes to enhance their innovative offerings. We define SAI as the organizational utilization of AI with the aim of incrementally advancing existing or developing new products, based on insights from continuously combining and analyzing multiple data sources. The designation of the concept as “*Self-innovating* AI” undermines that AI as a general-purpose technology will ultimately be able to innovate almost autonomously, i.e., without human interference, depending upon the products’ underlying degree of complexity. Our definition of SAI captures three important phenomena: First, it refers to the emerging practical phenomenon of firms increasingly relying on AI to enlarge their product spectrum [7]. Second, it is not limited to incremental innovations based on a firm's existing products but also includes the development of new products. Third, it includes the continuous combination and analysis of multiple data sources, comprising internal, external, and consumer-generated data. Thus, SAI transcends simply *innovating from data*, defined as “a centralized, firm-led process in which firms use digital tools to acquire, analyze, and act on consumer data to enhance their innovative offerings” [31, p. 682]. Thus defined, innovating from data involves unspecified digital tools utilizing consumer data but no further data sources. In contrast, SAI describes a specific technology that innovates using data from multiple sources, encompassing consumer-generated, external, and especially internal data, thereby also considering a firm's capabilities for innovation.

Our article seeks to make two unique contributions to the literature. First, we bridge the established perspective of firms’ innovation processes in the innovation management literature and current advances in AI in the computer science literature, answering recent calls to synthesize these two research streams [18], [19], [27], [39]– [41]. Currently, those scientists who study and implement AI agents into innovation processes “are predominantly the same scientists who have created the agents themselves” [41, p. 477], i.e., computer scientists. However, the opportunities and challenges enabled through integrating AI into the innovation process have not been covered through the innovation literature thus far. As theory has the overarching aim to explain and generalize real-world phenomena, the field of computer science can substantially inform innovation management research by considering that several firms are beginning to integrate AI into their innovation processes. In turn, a theoretically grounded conceptualization allows innovation management scholars to systematically analyze the opportunities and challenges of this phenomenon, and thus, to further inform the computer science discipline. With our SAI concept, innovation scholars are able to theoretically transfer the AI technology into an innovation context and eventually, to derive context-specific and theoretically grounded recommendations for further research in the field of computer science.

Second, our novel SAI concept expands understanding of how AI can help firms enhance their innovative offerings and, ultimately, achieve competitive advantage. While most innovation scholars are coherent in their recognition of AI as a potentially disruptive technology, they tend to remain unclear about AI's context-specific consequences and implications for the innovation process. With AI eventually evolving into a general-purpose technology with an almost unlimited area of applications, contextualizing AI seems crucial to move the innovation discipline forward toward a more specific and in-depth understanding of this unique technology. Our explicit theoretically grounded conceptualization of SAI enables a more fine-grained and contextualized understanding of how AI can be utilized with a specific objective, i.e., to innovate within organizations. Our contextualized theorizing recognizes SAI as a potentially disruptive phenomenon that is prevalent among several organizations and provides innovation management scholars with a profound guideline for further theory development.

The rest of this article is organized as follows. After defining the most relevant terms, we outline how firms may rely on SAI to incrementally advance existing or develop new products. Thereafter, we delineate how the spectrum of products, developable with SAI, will broaden from simple to increasingly complex as the technology matures. Finally, we offer suggestions for a range of emerging research themes on three different levels of analysis in this rapidly evolving domain and discuss managerial implications of the emerging utilization of SAI in an organizational context.

SECTION II.
Related Literature

To unravel the broad effects of SAI on a firm's innovation process, it is necessary to synthesize the innovation management and computer science perspectives in the literature. As a range of fundamental terms is often used differently and interchangeably both across and within these two research streams, explicit definitions are necessary to establish conceptual clarity.

A. (Big) Data

Data constitute the oil of the modern information age and, in the context of innovation, are a precondition for AI. Davenport [42] differentiates data from big data by noting that the former are analyzed with time delays, whereas the latter are processed continuously. However, the more common definition of big data refers to the amalgamation of multiple data points, which can be described along the three dimensions of *volume*, *variety,* and *velocity* (the "3 Vs"; [24], [29], [43]– [46]). *Volume* refers to the pure magnitude of data. Definitions of "big data"' are subject to constant change, as the amount of available data increases daily due to advancing storage technologies as well as growing data collection activities in general. For instance, Walmart, the world's largest retailer, collects and processes over 2.5 petabytes (i.e., 2.5 billion gigabytes) of data per hour, an almost unimaginable amount just ten years ago. However, practitioners are increasingly moving away from deducting the worth of data purely from volume, and focusing instead on the insights to be gained through data analysis [25], [47]. In this regard, high *variety* is important, referring to the heterogeneity of data sources. By combining multiple data sources, firms can reveal surprising and complex solutions for an almost indefinite number of problems. For instance, Walmart combines and processes hundreds of internal and external data sources, such as gasoline prices and weather forecasts, enabling the firm to accurately predict sales figures for each individual store. Finally, *velocity* refers to the speed of data creation and analysis. Creating and analyzing data in real-time clearly leads to competitive advantage, as firms can immediately respond to the market. For instance, Walmart analyzes its sales figures almost in real-time, and can detect anomalies such as increasing demand for a specific product before its competitors. In the best case, firms are capable of processing big amounts of data with high variety at great velocity [24].

As the 3 Vs increasingly provide a basis for establishing sustainable competitive advantage [24], many firms have implemented data-driven decision-making processes [48], [49]. However, there is scarce empirical evidence on how utilizing big data in decision-making processes influences the overall firm performance. For a sample of specific sectors in the U.S., Brynjolfsson *et al.* [50] find that firms adopting big data in decision-making processes have up to 6% higher productivity than would be expected from relying on alternative technologies. For the U.S. manufacturing sector, Brynjolfsson and McElheran [48] reveal that the average value added for data-driven decision-making adopters is 3% greater than for nonadopters, although this effect decreases over time. Müller *et al.* [51] employ a six-year panel dataset containing 814 firms listed on the U.S. stock market, and analyze the relation between big data analytics and a firm's financial performance. They find that big data analytics substantially increases firm performance, although the effects are only significant for firms in IT-intensive or highly competitive industries. Ghasemaghaei and Calic [29] empirically examine how each of the 3 Vs separately contributes toward firm innovation performance. They reveal that data velocity and variety play a critical role in enhancing firm innovation performance whereas data volume does not. In a German context, Niebel *et al.* [52] find that implementing big data analytics increases both the likelihood of a firm becoming a product innovator and the market success of its product innovations. Bharadwaj *et al.* [22] combine structured numeric data with large amounts of unstructured text data (over two million words extracted from movie critics' reviews), thereby significantly improving the predictive validity for box office respectively innovation success. Overall, the few empirical contributions imply a positive effect of big data utilization on firm performance. However, solely building on big data may also be harmful to firms, as big data analytics tools often mistake correlation for causation [25], [53]. Therefore, firms are increasingly seeking to overcome these causal fallacies by relying on AI to process data.

B. Artificial Intelligence

To solve real-world problems with machines, they need to be translated into arithmetic, i.e., digitally representable problems [54]. Historically, these endeavors were typically undertaken by mathematicians and software engineers who manually coded algorithms to tackle an ex-ante, specified, real-world problem. The manually coded algorithms would then be fed with data to generate the output, the accuracy of which depended on that of the mathematicians and on the software engineers' capability to translate real-world problems into arithmetic problems. By contrast, AI uses data not only as the input but also to derive the optimal arithmetic solution for a real-world problem without human interference. Put differently, AI uses data as the input, develops its own reasoning, and generates the output, i.e., the optimal solution based on the input. This explains why AI is viewed as such a disruptive and powerful approach: AI can learn almost infinitely—or, theoretically, until the derivation of exclusively optimal solutions—and can constantly self-adjust to changing data (or situations), just as humans do [55].

Due to the highly interdisciplinary nature of AI, which includes such fields as information science, anthropology, engineering, business, medicine, and linguistics, providing a widely accepted AI definition is challenging. Depending on the discipline, scholars categorize AI in terms of ability to imitate human behavior or thoughts or to behave or think rationally [12]. When perceiving AI as *acting humanly*, passing the so-called Turing test—developed by Alan Turing in the 1950s when AI was in its infancy—acts as a benchmark for intelligent behavior [56]. For this purpose, two humans (person A and an evaluator) and one machine are located in three distinct rooms. Person A and the machine perform written natural language conversations. The evaluator, who is aware that one conversation partner is a machine and one is a human, needs to reliably judge which of the two conversation partners is human. If the evaluator fails, the Turing test is considered passed.

Therefore, to pass this test, a machine needs to exhibit intelligent behavior indistinguishable from that of a human. This includes capabilities in natural language processing (to communicate in a given language), knowledge representation (to store knowledge), automated reasoning (to use stored knowledge to answer questions and solve problems), and machine learning (to adapt to new environments) [12]. *Thinking humanly*, in turn, refers to automatizing activities associated with human learning, decision-making, and problem-solving [57]. Whereas acting humanly focuses solely on the actual outcome, thinking humanly aims to imitate human thinking processes. However, acting or thinking humanly does not constitute the end of the intelligence continuum [58]. Due to the bounded rationality of humans [59], [60] and their limited cognitive information processing capacities [61], [62], AI-based machines that think and act rationally are expected to clearly outperform humans in a wide array of tasks (e.g., [1], [10], [63]). *Rationally thinking* AI overcomes the constraints of bounded rationality and limited cognitive capacities as it draws logical inferences with the aim of theoretically modeling rational human reasoning. However, in some situations, there is no provably ideal, logical inference to solve a problem [12]. While rationally thinking AI tries to develop the ideal, theoretical, logical inference without considering its real-world feasibility, *rationally acting* AI tries to develop the ideal possible solution within its environment. As rationally acting AI constitutes the most applicable field of research, we adopt Nilsson's [64, p. 13] seminal, and rather broad, definition of AI as an "activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment."

When discussing emerging digitization trends, two further terms are often mentioned and misused interchangeably with AI: *machine learning* and *deep learning*. *Machine learning* is not a distinct overarching research discipline but, rather, a subfield of AI [12]. It is defined as "a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty" [65, p. 1]. Put differently, software no longer needs to be coded manually with specific ex-ante determined instructions; instead, the machine is trained to optimally perform a task by relying on big data. *Deep learning*, in turn, is a branch of machine learning. LeCun *et al.* [66, p. 436] define computational deep learning as "representation-learning methods with multiple levels of representation, obtained by composing simple but nonlinear modules that each transform the representation at one level (starting with the raw input) into a representation at a higher, slightly more abstract level." Put differently, deep learning methods try to imitate the structure of a human brain to allow for solving highly complex functions [67]. Deep learning methods work by weighting each input on several dimensions according to how correct or incorrect it is for a given problem at each level of representation. The final solution to a problem constitutes the sum of all weightings. As weightings are based on experience, training the machine with big data enhances the accuracy and value of outputs generated through deep learning methods [68], [69].

The sudden dissemination of AI within organizations stems from two major recent developments. On one hand, AI relies on massive processing power capacities. Technological advances allow graphics processing units (GPUs) to supersede central processing units by allowing parallel computing, opening up completely new computational–analytical possibilities [70]. Additionally, GPUs are now comparatively inexpensive, and performing processing-intensive calculations has become feasible for not only tech giants but also small- and medium-sized companies. On the other hand, due to ongoing digitization, the availability of data has soared [24], [27], [44]. As AI continuously learns through trial and error processes, this increased availability of data leads to more accurate AI decisions. Therefore, increases in processing power capacities and data availability enable organizational utilization of AI.

Notwithstanding rapid advances, AI is currently still limited to narrow tasks such as skin-cancer detection [4], face recognition [71], and playing poker [72]. Accordingly, the primary aim of AI researchers is "the development of algorithms capable of general competency in a variety of tasks and domains without the need for domain-specific tailoring" [73, p. 235]. Such general competency would reduce the need for human adjustments and greatly enhance AI's value as a general-purpose technology [15]– [17]. In a service context, Huang and Rust [1] recently confirmed the current narrowness of AI and classify four different intelligences necessary to constitute a general-purpose technology: mechanical, analytical, intuitive, and empathetic. *Mechanical intelligence* refers to the automation of a specific task, and is typically applied in the field of robotics, whereas *analytical intelligence* describes the ability to process and learn from data to solve or predict tasks, e.g., future consumer purchasing behavior. At the next stage, *intuitive intelligence* is based on understanding and the ability to independently adjust to unknown situations and think creatively. For instance, IBM Watson is capable of correctly answering complex questions requiring a high level of contextual understanding and creativity. Finally, *empathetic intelligence* refers to the ability to learn from and appropriately (from a human perspective) respond to human emotions, e.g., in the same manner as psychologists. Despite rapid advances in all four intelligences, AI's current applications remain narrow and it is not yet a general-purpose technology [15], [73].

C. AI in Innovation Management

A myriad of articles have focused on the ongoing digitization of firms' innovation management activities in general (e.g., [18]– [21], [74]), and more recently on the merits of big data (e.g., [22]– [24], [26], [27], [44]) and 3-D printing (e.g., [30], [31]). Generally, Nambisan *et al.* [18] summarize that the digitization of innovation is increasingly challenging three well-established assumptions. First, innovation is no longer a well-bounded phenomenon, but instead characterized by unpredictability, dynamism, and fluidity. Second, the locus of innovation agency is shifting away from static centralization toward a widely distributed, less predefined state, including multiple collaboratively working actors. Third, innovation processes and outcomes are no longer seen as isolated entities but, rather, as dynamic and complex interdependencies. These developments necessitate novel theorizing on how specific digital technologies and their individual characteristics influence innovation, so as to enable more accurate explanations in an innovation context [18], [19].

In an innovation context, theorizing about digital technologies in general and AI in particular seems crucial for three reasons: First, AI's potential to develop into a general-purpose technology [15]– [17] will—unlike other digital technologies such as 3-D printing—disrupt *all* industries, ultimately resulting in a fourth industrial revolution [13]. Second, AI can help to overcome managers' and researchers' limited cognitive information processing capacities. Simon [75, p. 198] infamously stated that human decision-making is only imperfect because "[t]he capacity of the human mind for formulating and solving complex problems is very small compared with the size of the problems whose solution is required for objectively rational behavior in the real world—or even for a reasonable approximation to such objective rationality." In this line, Merendino *et al.* [26] recently conducted 20 semistructured interviews across the U.K., finding that senior managers are cognitively overloaded due to overwhelming amounts of big data, which ultimately compromises their overall decision-making. The authors suggest that senior managers must expand their cognitive capacities to deal with the challenges imposed by big data. In contrast to the human mind's capacity, AI's capacity for formulating and solving problems is almost unlimited. For this reason, Bharadwaj and Noble [28, p. 563] justifiably note that "managers may find that the rapid advances in artificial intelligence can provide them with the opportunity to outsource some tasks to algorithms" as AI can immediately detect key insights within data and thereby, in contrast to other digital technologies, directly support managers' decision-making. Clearly, also R&D workers may avail themselves of the opportunities emerging through the rapid advances in AI. At last and most importantly, AI is not just embedded into products or services but also increasingly deployed to develop products autonomously, i.e., to innovate [7]. This ability to innovate raises the need for novel theorizing to consider recent AI advances in an innovation context.

SECTION III. Self-Innovating Artificial Intelligence

Today, any product can be represented digitally [76]. This accounts for both the functionality [77] and physical structure [33] of a product. The digital representation of product functionality and structure enabled through new technologies allows the creation of digital twins of products [77]. Accordingly, Benner and Tushman [78, p. 505] state that products "can be created, represented, and modified with the same relative ease as software goods." Due to recent leaps in technology, products are increasingly created with AI [7]. We propose our SAI concept to enable innovation scholars to capture this phenomenon in a finegrained and contextualized manner. SAI constantly adapts to changing data and, thereby, continuously learns and improves its innovation outcomes with more experience. As SAI builds on a firm's internal data, external data, and consumer-generated data with the aim of incrementally advancing existing or developing new products, it is related to yet different from the intelligent agent concept. AI describes the study of intelligent agents—i.e., computer systems capable of undertaking flexible autonomous actions in order to meet a specified objective [12], [79]. Indeed, SAI comprises one or more system-embedded intelligent agents that act autonomously in order to achieve an ex-ante defined innovation outcome (e.g., to develop a new perfume). However, Feigenbaum [80, p. 3] famously remarked "that the problem solving power exhibited in an intelligent agent's performance is primarily a consequence of the specialist's knowledge employed by the agent." As SAI does not solely rely upon a specialist's knowledge – or, more broadly defined, upon a firm's internal data—but additionally autonomously acts upon external and consumer-generated data, the problem solving power goes far beyond the capabilities of an intelligent agent as defined by Feigenbaum [80].

Although this problem solving power is still limited, SAI's practical application within firms' innovation management activities is rapidly expanding as several firms begin to incorporate AI in their innovation processes. Davenport and Ronanki [7] surveyed 250 executives on the expected benefits of utilizing AI in an organizational context. More than half (51%) intended to use AI to incrementally advance existing products, while almost one-third (32%) named the development of entirely new products as a major goal. Table I provides several examples of how firms already use SAI within their innovation processes to enhance their innovative offerings.

TABLE I Practical Examples of Innovations Created by SAI

SAI	Description	Source
New product development	Researchers at the University of Münster, Germany developed an AI system that independently screens all 12.4 million known organic-chemistry reactions. The system can discover new retrosynthetic routes and simulate complex chemical reactions, which could revolutionize drug discovery.	[81]
	In collaboration with IBM, Symrise uses AI to create novel perfumes based on large historical datasets, including fragrance formulas and sales data.	[82]
	The biopharma company Berg recently introduced an AI platform which analyses patient biology and can discover differences between healthy and cancerous cells. The platform revealed naturally occurring patterns of molecules in cancer metabolism, ultimately paving the way for developing BPM31510, a drug currently being tested on people with advanced pancreatic cancer.	[8]
	Givaudan, based in Switzerland and among the world's largest cosmetic manufacturers, developed an AI-based new product development platform for cosmetics. The platform considers several parameters, such as the product launch region, regulatory compliance needs, market trends, type of ingredients, and retail price range; on these bases, it suggests the ideal composition of a new cosmetic product.	[83]
Incremental product advancement	Ohio-based Fabrisonic, which specializes in 3D metal printing using a low-temperature, ultrasonic, additive manufacturing technology, created a heat exchanger that is now being adopted in NASA's space programs. The new heat exchanger design was developed by an AI-based generative design software, and is both more efficient and 30% lighter than previous models.	[84]
	Titan Company, an Indian manufacturer of luxury jewellery, watches, and sunglasses (and part of the Tata Group), uses AI to improve existing and develop new product designs. For instance, AI identifies the latest colour trends in social media posts and pictures, and considers them in future product designs.	[85]
	The US online fashion retailer Stitch Fix relies on AI along the whole value chain, including product development. Its AI system decomposes each garment into several attributes, such as fashion, colour, or arm length, and combines consumer feedback with sales and further data for each attribute. By recombining and improving the most promising attributes, products are incrementally improved and passed on to human designers, who then make final modifications.	[86]

Several scholars have acknowledged that digital technologies increasingly transcend their initial role as an innovation-supportive operand resource but, rather, act as an operant resource, i.e., actively contribute to the innovation outcome (e.g., [2], [35], [40]). In contrast to operand resources, operant resources are generally intangible and characterized through dynamically acting on other resources rather than being acted upon [2]. Importantly, SAI does not constitute an operand resource as it does not refer to products and services with embedded AI, such as autonomous cars, natural language processing applications or skin-cancer detection systems. Instead, SAI refers to a firm-led, AI-based development or advancement of a product, and thus, describes an operant resource. SAI as an intangible and dynamic operant resource creates new value actively due to its inherent capability to incrementally advance existing or develop new products and, therefore, serves "as an active ingredient in fueling innovative initiatives" [40, p. 2].

According to Cockburn *et al.* [17], AI constitutes an invention of a method of inventing, as first described in Griliches' [14] seminal work on hybrid corn. Griliches [14] inductively revealed that some chosen inventions do not simply constitute an isolated invention for themselves or can be used for incrementally advancing existing or developing new products; instead, they can incrementally advance or develop new products with a broad range of applications. As hybrid corn may not only be used to develop a specific new corn variety but also has a broad range of applications by being able to breed several different new varieties, it constitutes an invention of a method of inventing due to its wide-scale applicability on agricultural breeding as a whole. As with hybrid corn, SAI may be understood as not merely a method to solve a specific problem but, rather, a new, generable approach enabling innovation across a wide range of fields [17]. Due to recent leaps in development, SAI has the potential to transcend its initial field of solely solving specific problems by incrementally advancing existing or developing new products with a broad range of applications, based on insights gained through continuously combining and analyzing multiple data sources, and thereby fundamentally changing how innovations are created.

Ideally, SAI can draw on multiple data sources, including a firm's *internal data*, *external data,* and *consumer-generated data,* to incrementally advance existing or develop new products. *Internal data*—produced internally as a direct or indirect result of a firm's business operations—include data about employees, corporate resources, productions lines, suppliers, management decisions, sales and marketing figures, products, and a firm's overall capabilities [87]. With a firm's digitized internal data, SAI can consider the overall capabilities when incrementally advancing existing or especially developing new products, and thereby innovate within the firm's scope. For example, firms need to explicate their production line capabilities so that SAI develops products that are both theoretically and practically manufacturable [77].

SAI can also build on *external data,* namely those obtained from external sources over which a firm has little or no direct control, and including but not limited to market, competitor, media, macroeconomic, and environmental data [87]. Sources of external data are manifold and include, for example, the following:

1) governmental institutions such as the US Census Bureau;

2) public, nongovernmental organizations such as the OECD or the UCI Machine Learning Repository;

3) databases from private companies such as Google Finance or the New York Times.

External data is integral to a firm's data stock and increases firm innovativeness [44], [88]. SAI uses external data to complement a firm's internal data and consumer-generated data, enabling the detection of previously unknown patterns and the identification of new opportunities, on which bases SAI ultimately acts intelligently to incrementally advance existing or develop new products.

Consumer-generated data, as a hybrid between internal and external data, is defined as data created through consumers directly or through firm-consumer interactions. Consumers contribute both actively and passively to SAI in several ways. Consumers can actively contribute to SAI through awareness of being involved in a firm's innovation process. For example, Hoornaert *et al.* [89] disentangle how crowdsourcing consumer-generated ideas via direct participation significantly enriches new product development. Similarly, Mahr and Lievens [90] show that data gathered through virtual lead user communities can enhance a firm's innovativeness, as lead users are at the forefront of the market and can precisely articulate their needs and desires. On the other hand, consumers may contribute to SAI without awareness of being involved in an innovation process. A range of articles has shown how consumer-generated data in the form of online product reviews and social media posts—which typically aim to rate existing products, rather than to develop new products—can be systematically analyzed to gain deeper insights into consumers' product satisfaction (e.g., [91]– [95]). For example, Roberts *et al.* [94] empirically demonstrate that firms benefit from analyzing social media posts as they gain access to novel information about customer preferences and products, which ultimately leads to higher overall innovation performance. However, consumer-generated data may also be collected passively through tracking activities such as online tracking [96], health tracking [97], and geospatial tracking [98], thereby providing deeper insights into actual consumer behavior. Overall, SAI may build on data gained through both actively and passively contributing consumers to incorporate consumer preferences and desires into future products.

The following example underlines how SAI combines internal, external, and consumer-generated data with the aim of developing a new product. Imagine a firm using SAI to develop a new perfume for a previously untargeted market. This firm may use SAI to classify its current perfume product line along a range of tangible and intangible attributes. Tangible attributes may include the perfume's scent or color, or the flacon's size; intangible attributes may comprise the combination of fragrance formulas or the complexity of each perfume in the product line. Subsequently, SAI may complement the identified values of both the tangible and intangible attributes with further data, such as each perfume's historical sales figures, consumers' online activities (e.g., website tracking, social media posts, product reviews), and consumer ideas actively generated through crowdsourcing. Additionally, SAI may use external data to develop the new product. As perfume preferences tend to differ across different climates and cultures [99], SAI may include climate or cultural data (e.g., along the cultural dimensions classified by Hofstede [100]), together with further data which may influence consumers' perfume preferences. Based on the insights from combining these multiple data sources, SAI may determine an optimal ratio of each of the attributes, given the firm's capabilities, and ultimately develop a new perfume that ideally fits the new market's consumer preferences. In fact, Symrise—a major German producer of flavors and fragrances—is currently collaborating with IBM on SAI that can develop new fragrances based on fragrance formulas, sales figures, and other data sources [82].

However, SAI may not only be used to develop entirely new products but also to incrementally advance a firm's already existing products. For example, Titan Company—an Indian luxury goods manufacturer and part of the multinational Tata Group – uses SAI to incrementally advance existing product designs [85]. For this purpose, its SAI identifies several attributes such as the latest color trends in social media posts, adapts these attributes to the company's current product range, and considers them for future product designs. Consequently, Titan Company is able to achieve a competitive advantage due to its fast response to altering consumer preferences.

SECTION IV.
Current State and Prospects of SAI

Clearly, the organizational implementation of SAI will not arise suddenly but successively in line with AI's further advancement. Currently, AI development is accelerating, and further significant progress can be expected in the very near future [9]– [13]. Accordingly, the spectrum of products that can be developed with SAI will broaden from simple to increasingly complex. Product complexity refers to several dimensions, including the design and number of a product's components, the design and number of interdependencies between the components, the degree of component customization, and the knowledge required to develop and interconnect the components [101]. Obviously, the degree of product complexity can range from very simple (such as clothing) to highly complex (such as an aircraft). Low-complexity products are characterized by limited knowledge being necessary for product development, a simple design with only a few components, limited component interdependencies, and low customization. At its current stage, SAI is only capable of developing low-complexity products, which still require significant adjustments by humans. For example, the U.S. online fashion retailer Stitch Fix relies on SAI to decompose each of the firm's garments into several attributes, such as style, color, or arm length, which it combines with consumer feedback and sales data. Subsequently, SAI recombines and improves the most promising attributes, and passes its suggestions to human designers who make some final modifications [86]. As SAI evolves, the necessity of human adjustments to SAI-developed low-complexity products decreases, with SAI able to take over an increasing number of tasks previously performed by humans. Eventually, SAI will be able to create simple products autonomously, i.e., to innovate without human interference.

As SAI further advances, SAI-developed products will become increasingly complex. Products with high complexity are characterized by the need for profound knowledge about and deep understanding of each individual component, interdependent components, complex design, and high customization. At its current stage, SAI cannot develop highly complex products due to its narrowness and inability to fully grasp complex interdependencies. However, even in the stage of low advancement, firms may integrate SAI into innovation processes to support humans developing highly complex products. Currently, human-supporting machines are predominantly employed in the ideation process. For example, Christensen *et al.* [102] show how machine learning can be used to scan online communities with the aim of detecting posts that contain new product ideas. Toubia and Netzer [103] demonstrate that insights from analyzing consumer-generated ideas with big data analytics tools can be used to support human creativity new product development teams can be given the most promising product ideas or keywords that complement the teams' ideation process. In the same vein, Hoornaert *et al.* [89] delineate how machine learning algorithms can evaluate and rank consumer-generated ideas, which significantly reduce the effort required to screen ideas.

However, with further advances, SAI is likely to shift from supporting toward more closely collaborating with humans developing complex products. This AI–human collaboration with the aim of completing a task is commonly termed "augmentation" [104], [105]. While it seems highly unlikely that SAI could create complex products autonomously, it may develop isolated components or significantly enhance a product's design. Brynjolfsson and Mitchell [106] note that machines already outperform humans when designing complex products and delineate how SAI developed a new heat exchanger that exceeds previous humanly developed heat exchangers in all classified dimensions. The authors argue that such creative design tasks will be increasingly performed by machines. However, the dimensions for the new products' design need to be well specified. For example, R&D workers clearly specified the heat exchanger's maximum weight and its minimal cooling rate. Thus, future R&D workers need to adapt to these changes imposed by SAI and be able to precisely specify the new complex product's dimensions by articulating the right questions and the desired outcome [106].

SECTION V.
Agenda for Future Research

Despite continuously increasing practical applications of AI within an organizational context, prior innovation literature has mostly overlooked these recent advances so far. Due to AI's distinctiveness from other digital technologies, future research is recommended to re-evaluate the applicability and the boundary conditions of well-established theories in the light of SAI. Furthermore, especially qualitative-empirical case studies may be a promising way to inductively generate new theories, taking the idiosyncratic nature of AI into account. More specifically, further research that profoundly illuminates how SAI influences a firm's innovation activities seems necessary on at least three different levels of analysis. These include how SAI will impact R&D workers, how SAI may influence the innovation process, and issues regarding the overall organizational strategy. We outline these areas for future research in Table II.

TABLE II Research Agenda for SAI in Innovation Management

Level of Analysis	Area for Future Research	Sample Research Questions
Individual	Skills and Tasks	• How does the implementation of SAI into the innovation process affect the nature of tasks traditionally performed by R&D workers? • What skills will become more important for R&D workers? • What tasks can SAI and R&D workers pursue together, and how are these tasks to be orchestrated? • Is there any job replacement effect? • To what extent can SAI help R&D workers to focus more on developing more complex products?
	SAI Adoption	• How do R&D workers perceive the organizational implementation of SAI? What challenges do they face? • What determinants increase the acceptance of SAI by R&D workers? • To what extent can R&D workers decompose and identify with SAI-developed products, and what are the consequences?
Innovation Process	Speed	• How does SAI change the time in which innovations are created? What opportunities and challenges arise through a change in the speed of innovation? • To what extent can SAI perceive altering consumer prefences and what is the right time to develop a new product based on these changes? • How does SAI impact the time-to-market of newly developed products?
	Openness	• How does SAI change the actors that participate in the innovation process? How does SAI impact the way in which these actors pursue innovation together? • How does SAI alter the connection between innovation process and outcome?
	Structure	• At what stages of the innovation processes can SAI be implemented? How does SAI change the nature of traditional innovation process structures, such as idea generation, idea selection, or product development? • How and to what extent does SAI affect the allocation of resources to different stages in the innovation process? • With SAI developing simple products autonomously, can firms allocate more resources towards the development of more complex products?
Organization	Innovation Strategy	• How and why does SAI impact a firm's overall innovation strategy? • Does SAI affect whether firms pursue an exploitative or an explorative innovation strategy? How can firms achieve ambidexterity when relying on SAI? • What kind of data does SAI need to develop more radical products?
	Market Strategy	• How do incumbent firms need to adjust their business models in light of SAI? What opportunities and challenges emerge for young ventures? • Do firms need to allocate more resources to digitalize their knowledge, and what kind of data is most valuable for SAI to act upon? How can firms use the market to build up a more comprehensive data stock? • What industries are most affected by SAI, and why? How does SAI change the overall rules of the market?

A. SAI's Impact on the Individual Level

Clearly, the organizational implementation of SAI will not only alter how innovations are created but also how the role of R&D workers in the innovation process changes. Because SAI is expected to take over an increasing number of tasks previously performed by humans, R&D workers may need to adjust their skills and abilities. AI is expected to replace humans in a vast number of jobs (e.g., [10], [63], [107], [108]). Most scholars concur that job replacement will occur gradually as AI advances and eventually replace human workforce at the task level entirely [1], [104]. In this line, Brynjolfsson *et al.* [15] argue that AI requires a significant reorganization of the content of jobs, shifting from purely automatable toward highly variable and complex tasks. Depending on task variability and complexity, AI and humans may interact with each other in a transition stage, with jobs executed partially by a human and partially by AI [104], [109]. With the organizational utilization of SAI, job reorganization will also affect the skills and abilities required by R&D workers [110]. As AI matures, the complexity of products developed autonomously by SAI will gradually increase. Therefore, R&D workers need to adapt to these changes by acquiring skills and abilities that SAI struggles to imitate. Further research should develop a theory of job replacement with a clear focus on innovation management, considering the future skills and abilities needed by R&D workers, thus emulating the meticulous work by Huang and Rust [1] in the field of service.

Furthermore, building upon the previous research implication, further research should also focus on the individual technology acceptance of SAI by R&D workers. Technology acceptance describes the degree to which a firm's employees accept and use a technology developed by others [111]. Generally, employees tend to be sceptical about the implementation of new technologies as they are perceived as a threat to their autonomy and, ultimately, their jobs (e.g., [112]). As SAI is expected to significantly affect the autonomy and content of R&D workers' jobs [110], it seems likely that R&D workers will be highly sceptical toward its organizational implementation. From an organizational perspective, the employees' technology acceptance determines the success or failure of the newly implemented technology [113]. As firms relying on SAI are likely to achieve a competitive advantage, it is, therefore, critical for firms to increase SAI's acceptance by its R&D staff. Thus, further research should explore the applicability of well-established technology acceptance models (e.g., [114], [115]) in light of SAI and identify further potential determinants that increase SAI‘s technology acceptance of R&D workers.

B. SAI's Impact on the Innovation Process Level

Infusing new digital technologies into the traditional innovation process alters how innovations are created (e.g., [18], [19], [33]– [35]) and we expect that the same accounts for SAI. More specifically, we believe that further research should illustrate how SAI changes the innovation process in three broad areas: speed, openness, and structure.

First, SAI is likely to further accelerate product development processes. Using digital technologies in innovation processes tends to significantly increase innovation speed (e.g., [116], [117]). SAI may further increase innovation speed by analyzing and combining multiple data sources in real-time, thereby immediately reacting to shifts in consumer preferences. This means that a firm relying on SAI can respond to preference changes before its competitors, thus achieving competitive advantage. However, when more than one firm in a given market relies on SAI, the time-to-market for SAI-developed products becomes crucial to achieving competitive advantage. Consequently, competition in reducing new products' time-to-market is likely to intensify further [118]. However, shorter product development processes and a shorter time-to-market may not always have a positive effect on the success of an innovation [119]. For example, SAI may innovate on the basis of short-lasting market trends (as often found in the fashion industry) and therefore create products that are obsolete when reaching the market. Thus, further research could explore the challenges posed by SAI-led accelerated product development processes.

Second, SAI may alter the openness of the innovation process. Openness refers to the notion that firms can enhance their innovativeness by integrating external actors into the innovation process [120], [121]. With the boundaries of the innovation process becoming more porous and fluid, firms can purposively combine external ideas and knowledge with their internal capabilities. Generally, digital technologies have significantly contributed to increasing the openness of the innovation process [18], [40]. For example, digital technologies such as 3-D printing enable firms and consumers to co-design and co-manufacture products, thus blurring the traditional separation between both the physical and the digital as well as the creator and the recipient of value [31]. With SAI, the openness of the innovation process may be further increased as it relies on data from multiple sources, encompassing consumer-generated, external, and internal data. In order to gain access to more valuable data sources, firms may need to integrate the data contributors more deeply into their innovation process. However, with further opening of the innovation activities to external actors, firms typically need to reveal larger parts of their own data [122]. Thus, further research should strive to identify the optimal degree of openness in the context of SAI. This also includes to identify which actors should participate to what extent in the innovation process and how to orchestrate the different goals and motives of these actors when pursuing a SAI-developed innovation collaboratively.

Third, SAI may influence the general structure of the innovation process. Today, several firms have implemented an open innovation process which is characterized through involving both internal and external actors in a wide array of different stages, ranging from the initial idea generation/selection over research and development to product commercialization [121]. Generally, infusing digital technologies into the innovation process makes it difficult to precisely define when a particular stage starts and/or ends [19]. As SAI continuously combines and analyzes multiple data sources, the innovation process may become even more dynamic and fluid. More specifically, SAI may change the fluidity in different stages of the innovation process in various ways. For example, at its current stage of development SAI is predominantly employed in the ideation process, such as filtering product ideas from online communities [102] or evaluating and ranking ideas [89], [103]. With the possibility to systematically screen and evaluate an almost infinite number of ideas, new challenges for the ideation process as well as subsequent stages in the innovation process emerge, such as how and when to adapt these ideas to products which may already exist. Thus, further research is advised to analyze how SAI changes the nature of the traditional innovation process, and how to design an environment in which SAI can innovate effectively. Additionally, with the changing structure and fluidity of the innovation process, firms may also need to adjust their allocation of resources to different stages in the innovation process. For instance, at its current stage of development SAI may significantly enhance the degree of automatization of a firm's ideation process, thus enabling the firm to allocate more resources to other stages of the innovation process. Therefore, further research is advised to examine how SAI changes the allocation of and requirements for different resources needed at different stages in the innovation process.

C. SAI's Impact on the Organizational Level

Because SAI alters the overall way in which innovations are created, firms may need to adapt to these fundamental changes not only on an individual and process but also on an organizational level. For this purpose, we propose two broad research topics related to how SAI may change the organizational innovation strategy, and the overall market strategy.

First, with SAI firms may need to change their overall innovation strategy as they struggle to learn ambidextrously. Ambidextrously learning firms are able to simultaneously engage in exploitative (incremental) and explorative (radical) innovation activities [123], [124]. As SAI primarily relies on data to innovate, radical innovations may face systematic discrimination as they are characterized by novel methods, ideas, and materials for which no data sources exist [125]. In contrast, the major source for incremental innovations is a firm's already established database, on which SAI can build. Therefore, firms may tend to rely on SAI to develop incremental innovations and simultaneously invest in an environment that facilitates radical innovations. Future research should focus on the extent to which firms should adjust their innovation strategy in light of SAI to achieve ambidexterity. This also includes exploring what kind of data SAI needs to develop incremental respectively more radical innovations.

Second, severe strategic implications for both new firms and incumbent firms concerning their overall market strategy may arise. AI is expected to disrupt entire markets and industries, which ultimately may result in a fourth industrial revolution [13]. With SAI generating previously unknown explanations and inventions, possessing a comprehensive data stock serving is likely to become imperative for both new and incumbent firms in order to gain competitive advantage. In contrast to incumbent firms, new firms are typically equipped with only limited resources and, therefore, limited data access. Consequently, with SAI's further advancement, incumbent firms may be strengthened in their market position as the entry barriers for new firms increase. At the same time, SAI may lower the experimentation costs for new firms to develop new products and, thereby, decrease the entry barriers for new firms. Most likely, SAI's specific consequences will vary by industry as some industries tend to be more prone to these disruptive rearrangements than others. For example, new firms in the medical sector increasingly rely on SAI to develop new products (e.g., [8], [126]), whereas the aeronautic industry is not subject to SAI-developed products so far and, instead, is dominated by incumbent firms. However, both new firms and incumbent firms will most likely need to adapt to these changes by adjusting their business models to these new underlying rules of the market. Concluding, further research is advised to examine SAI‘s strategic implications for both incumbent and new firms and to identify further industry-specific variables that may affect their strategic choices.

SECTION VI.
Conclusion

SAI is set to severely impact firms by fundamentally changing the overall way in which innovations are created. While the organizational implementation of SAI into the innovation process has just begun, further advances will lead to more firms integrating SAI more deeply into the innovation process, aiming to incrementally advance existing and develop new products. Firms relying on SAI may achieve competitive advantage for several reasons: First, the automation of tasks enables a shift in resource allocation, giving R&D teams more time to concentrate on developing complex products, with simple products increasingly created through SAI. Thus, firms implementing SAI are likely to achieve competitive advantage through more efficient resource allocation. Second, SAI can detect and translate emerging market trends into new products in real-time. Through immediately reacting to altering consumer preferences, firms relying on SAI gain a time advantage over competitors. Third, with managers and R&D workers increasingly constrained by overwhelming amounts of big data, SAI may help them to overcome data chaos as it does not face the obstacles of bounded rationality and limited cognitive information processing capacities. Accordingly, SAI is expected to detect and intelligently act upon previously unknown patterns to generate new explanations and inventions, eventually leading to competitive advantage.

However, many implications remain vague, with the organizational implementation of SAI still at an early stage and most effects not yet observable. As AI's current applications remain narrow and do not yet constitute a general-purpose technology, Turing Award winner and recipient of the *IEEE John von Neumann Medal*, John Hopcroft [127] recently described AI's current limitations as “pattern recognition in high dimensional space.” Although pattern recognition is believed to lie at the very basis for developing new products and services—a cognitive process that Baron [128, p. 111] refers to as “connecting the dots” between external events and trends—at its current stage of development SAI is only capable of developing low-complexity products due to its narrowness and inability to fully grasp complex interdependencies. Therefore, at the present time, firms are advised not to perceive SAI as a substitutional but rather as a complementary technology for their established innovation activities. In order to integrate SAI into the innovation process more deeply, scholars and practitioners will need to further elaborate on the opportunities enabled through SAI, as well as on the managerial challenges typically concomitant with such disruptive technologies.

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