Data-Driven Innovation: What Is It?

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Abstract

The future of innovation processes is anticipated to be more data-driven and empowered by the ubiquitous digitalization, increasing data accessibility and rapid advances in computing, machine learning, and artificial intelligence technologies. While the data-driven innovation (DDI) paradigm is emerging, it has yet been formally defined and theorized in the academic literature and often confused with several other data-related phenomena. This paper aims to crystalize "data-driven innovation" as a formal innovation process paradigm, dissect its value creation, and distinguish it from data-driven optimization (DDO), data-based innovation (DBI), and the traditional innovation processes that purely rely on human intelligence. With real-world examples and theoretical framing and reasoning, we elucidate what DDI entails and how it addresses uncertainty and augments creativity in the innovation process. We also discuss the strategies and actions that innovators, companies, R&D organizations, and governments can take to embrace the future of data-driven innovation.

Keywords: Innovation Process, Uncertainty, Creativity, Data Science, Machine Learning, Artificial Intelligence

1. The Uncertainty Challenge to Innovation

In today's fast-evolving world, companies and R&D organizations must restlessly innovate new technologies, products, services, and systems to address evolving societal needs, drive growth, and stay ahead of competition. However, innovation is never easy or assured, because of the innately uncertain nature of the innovation process. The aim of innovation is to create new products, new demands, and new markets. In turn, the creativeness and newness that define innovation also result in uncertainty in the process of pursuing innovation. It is often ambiguous what to innovate and how to innovate. Uncertainty surrounds the innovation process and challenges all innovators and companies.

Meanwhile, the digitalization of our work and life have been generating growing data about technologies, processes, users, markets, etc., daily, hourly, and second-by-second. If we can properly mine, analyze and make sense of such data, particularly the naturally and often passively generated digital footprint data, in principle we will be able to make innovators more inspired and innovation decisions more informed, and thus reduce the uncertainty and increase the creativity in the innovation process. This is the "Data-Driven Innovation (DDI)" process. The rapid advances in artificial intelligence and computing power will further empower data-driven innovation.

The term "data-driven innovation" has appeared in both lay press and a small number of reports and papers in the past few years but was given different meanings [1,2]. The concept is often confused with the innovative products and services whose core features and value creation for users are based on data (which we will call data-based innovation) [3,4,5], or with the innovative operations which mine and analyze data to optimize efficiency and accuracy in delivering pre-defined objectives (which we will call data-driven operation) [6,7,8]. Such ambiguity might limit or misguide the actions and efforts aimed to make the innovation processes more data-driven, informed and inspired for greater creativity.

Therefore, this perspective article is aimed to dissect data-driven innovation as a process and distinguish it from other data-related paradigms. We will first start with a few real-world examples of data-driven innovation and theoretical analysis on what DDI entails and how it creates values by reducing uncertainty and augmenting creativity in the innovation process. On this basis, we will also discuss various technological, organizational and policy considerations to embrace and prepare for the future of innovation processes that are data-driven and AI-empowered.

2. What Is Data-Driven Innovation: Some Real-World Examples

One example of data-driven innovation is when Intuit created Quickbooks, an accounting management software for small businesses. The idea was conceived when the team analyzed the digital footprint data of users for their earlier product Quicken, a personal financial management software, and found many customers used Quicken in workplaces for business accounting. Then the team developed a new product specifically for small business accounting, which was the Quickbooks [9]. In this case, the inspiration for innovation was obtained from rather simple user digital footprint analytics. In fact, DDI can be further empowered by advanced big data computation, machine learning and artificial intelligence technologies.

For instance, IBM conducted a large-scale semantic analysis of millions of public text documents about diverse materials to identify three natural materials which have never been used in a battery and are unknown by battery engineers and combined them in a new battery design that outperforms state-of-the-art lithium-ion batteries [10]. In another example, Atomwise, a San Francisco-based drug discovery startup, trained neural networks on large-scale prior experimental data to predict the performance of new drugs to accelerate drug innovation [11]. Since the outbreak of COVID-19, researchers around the world have been racing to develop medical cures and vaccines. Many have taken a data-driven approach to mine large databases of compounds, peptides, and epitopes to train machine learning models to discover, generate and evaluate vaccines and candidate cure medicines [12].

Enormous data that can be mined to aid innovators are publicly available and accessible everywhere in our digitalized life. For instance, e-commerce websites host massive publicly accessible data about products, users, and their opinions about products. Researchers have mined data from e-commerce websites to train neural networks that can learn the latent needs of consumers, based on their comments on consumer products and translate such into technical design requirements to inform product design [13]. In fact, mining and analyzing consumers' behavior and opinion data from e-commerce sites, social media, and other online or digital spaces to inform new product development has been a common practice and well-studied in the marketing literature.

In the meantime, the digital footprints of innovators and innovation activities may also inform and inspire innovators and companies for innovation. For example, the public patent database contains enormous unstructured multimodal descriptions of prior technologies across domains and digital footprints of inventors and companies regarding their innovation behaviors and performances. There have been efforts to develop patent data-driven expert systems to inform companies of latent innovation opportunities specifically for them [14] and retrieve and prompt design stimuli from the patent database to inspire innovators for generating new design ideas [15], as well as to train neural networks with patent data to predictively evaluate the value of new inventions [16].

The US Chamber of Commerce Foundation [2] highlighted four types of open big data that can be explored to generate value across sectors. They include user-generated data (often online), industrial and sensor data (from GPS, mobiles, machines/equipment, and public infrastructure), business or enterprise data (such as inventories and transactions), and public data (curated or generated by government agencies, universities, or non-profit organizations, such as patents, papers, reports). Such open and public data sources, as well as the proprietary data of companies and government agencies, may enable enormous opportunities for data-driven innovation.

3. How Does DDI Create Value: A Theoretical Explanation

3.1 Dissecting the Innovation Process

These aforenoted examples demonstrate various ways or manners in which data-driven approaches can inspire, inform, and augment a variety of creative but uncertain activities in the innovation process. Here we further crystalize how data-driven innovation works and creates value for the different and complementary actions in typical innovation processes. To aid the analysis, we dissect an innovation process into four typical process actions contributing to two value creation humps (Figure 1). Please note that, real-world innovation processes are more complex and involve additional actions, such as business planning and physical embodiment development. The double-hump model here focuses on the core creative actions.

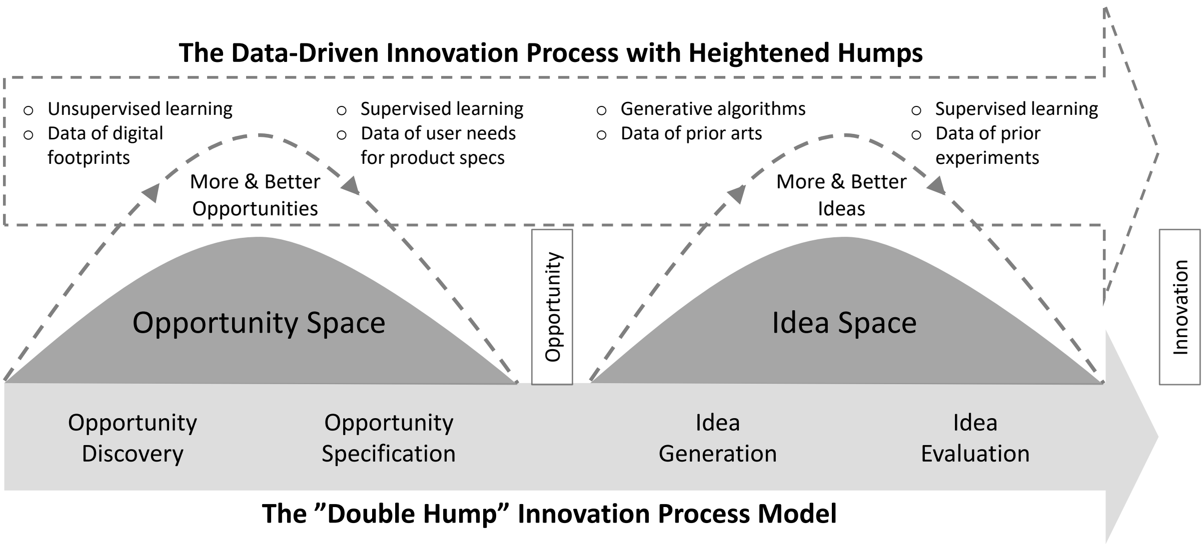

Figure 1. Data-Heightened Opportunity and Idea Humps in the Innovation Process.

The first hump represents the innovation opportunity space. The opportunity space exits latently but needs to be discovered via the exploration of latent human needs that are unmet. Then specific opportunity needs to be identified and defined with clear requirements to enable idea generation to address it. Therefore, the opportunity space hump is shaped by the two actions including opportunity discovery and opportunity specification.

The second hump presents the innovation idea space. The idea space does not exist previously and needs to be created via the generation of many, diverse new ideas to address the specified opportunity. Then the generated new ideas need to be tested, evaluated, and validated in terms of how novel, useful, and feasible they are. As a result, the idea space hump is shaped by the two actions including idea generation and idea evaluation.

It is important to note that the two-hump four-action process presented involves feedback and iterations not shown in Figure 1. For instance, one might perceive and discover additional opportunities during idea generation. New ideas can also be generated with the feedback and learning obtained during evaluation and validation. The real-world innovation processes are non-linear, iterative, and adaptive by nature, despite sharing the common creative actions in Figure 1.

Higher opportunity and idea humps indicate greater upper bounds of the innovativeness and value creation from the innovation process. Although a company or innovation team often, due to resources constraints, only acuate a small number of new ideas to address a small number of opportunities, discovering a more diversified scope of opportunities and generating a greater variety of ideas at the first place may ensure higher values of the best opportunity and greater innovativeness of the best idea.

3.2 How Data-Driven Approaches Can Create Value for Innovation

Thus, to heighten the humps, greater divergence in opportunity discovery and greater variety in idea generation are beneficial. In result, the heightened humps (or the expanded opportunity and idea spaces) would further require more efficient opportunity specification and idea evaluation to converge towards the most valuable opportunities and most innovative ideas to acuate. The double hump model synthesizes and highlights the specific divergent or convergent actions, and suggests different data sources and data-driven methods that are needed to inform, inspire, and augment the respective actions (Table 1).

Table 1. Data-Driven vs. Human-Social Approaches to Innovation Process Actions

Innovation Process Actions	Human-Social Approaches	Data-Driven Approaches
Opportunity Discovery	Interviews, surveys, observations of people to discover needs, problems, frustrations, and challenges as innovation opportunities	- Unsupervised learning - Digital footprint data about users and/or innovators - Enlarged opportunity space
Opportunity Specification	Intuitive human expertise is required to specify design requirements based on user needs.	- Supervised learning - Integrated data of user preferences of product specifications - Accelerated and accurate opportunity specification
Idea Generation	Individual ideation, gut feeling and social processes such as brainstorming and crowdsourcing to generate new ideas	- Generative algorithms - Databases of prior arts or knowledge - Enlarged idea space
Idea Evaluation	Experiments with users engaged to evaluate and validate the new ideas	- Supervised learning - Data of prior experiments - Accelerated idea validation

For *opportunity discovery*, the traditional approaches involve interviewing, surveying, or observing people to develop empathy and understand their needs, problems, frustrations, and challenges. By taking a data-driven approach, innovators may mine and analyze the users' digital footprints of using or commenting on existing products or services to gain insights on the unmet needs (e.g., Quicken [9]). Innovators can also explore the digital footprints of their own in the innovation process to gain insights on the unexplored applications of their technologies as innovation opportunities (e.g., InnoGPS [14]). Opportunity discovery is an exploratory action by nature and thus best supported by unsupervised machine learning techniques.

For *opportunity specification*, innovators often rely on human expertise to translate the insights about people and needs gained from the discovery phase into specific design requirements that can direct idea generation. In contrast, a data-driven approach can better cope with the opportunity uncertainty especially when the latent opportunity space is large and complex, by making innovators more informed when they evaluate and select opportunities for further pursuits [17]. For instance, innovators may utilize the digital footprint data of user preferences together with the design specifications of the products they purchased, used, or liked (e.g., from e-commerce sites) to train artificial neural networks that relate the former to the latter. Then such trained artificial neural networks can be used to automatically translate newly discovered user needs to specific design requirements [13]. Such actions are translational by nature and thus best supported by supervised machine learning techniques.

For *idea generation*, traditional processes rely on human expertise, gut feeling, or social processes such as brainstorming and crowdsourcing to tap on crowd human intelligence. By taking a data-driven approach, innovators may obtain inspirations from data repositories of prior designs and inspiration sources, e.g., asknature.org, moreinspiration.com and patent database that store the knowledge and concepts from millions of inventors, to stimulate creative ideation [15]. Further, computer algorithms can automatically generate new ideas by mutating, combining, and recombining prior concepts from large knowledge databases [18]. For instance, genetic programming algorithms may start from a small set of initial ideas to generate alternatives that better satisfy a pre-defined fitness function [19]. With the rapid advances of deep learning in the past decade, the neural network-based generative adversarial networks (GAN) have shown the ability to efficiently generate many and more novel designs that deviate from the training data [20].

For *idea evaluation*, traditionally companies and innovation teams develop minimum viable products and engage external lead users for testing and feedbacks. Such processes are expensive, time-consuming, and serendipitous. By taking a data-driven approach, innovators can automatically evaluate and validate a very large quantity of diverse ideas to accelerate the idea evaluation and validation process. For instance, innovators can automatically evaluate and filter many new ideas with a pre-trained common-sense knowledge base [21]. One can also train deep neural networks with the data of prior experiments or successful/failed designs in the same context for automatically and predictively evaluating the performances and value of next design ideas (e.g., Atomwise [11]; [16]).

In brief, unsupervised learning of digital footprint data may help explore and discover a bigger opportunity space than what humans could perceive on their worn. Innovators drawing inspirations from large knowledge databases (e.g., patents, papers) and using data-driven generative algorithms may create a bigger new idea space than what humans alone could conjecture up. Meanwhile, data-trained models may automate the evaluation of the opportunities [17] and new ideas [21] from the enlarged opportunity and idea spaces and accelerate the convergent search and identification of the best innovation opportunity and solution idea for realization. Therefore, both divergence- and convergence-oriented actions in the innovation process can be augmented by suitable data-driven approaches and together augment the creativity of the innovation process.

4. What Is Not Data-Driven Innovation

To define data-driven innovation as a formal process paradigm, we need to distinguish it from other seemly related paradigms or phenomena. Data-driven innovation is the process of innovating that is data-driven to make innovators and their activities and decisions more informed, inspired, and more creative – whether by applying data science, machine learning or artificial intelligence (AI) to large-scale data of users, innovators or more stakeholders. It contrasts with the traditional innovation process that relies on human expertise (creative genius), social activities (brainstorming, crowdsourcing, open innovation), and serendipity.

The data-driven innovation (DDI) paradigm should not be confused with data-based innovation (DBI), which refers to an innovation process's creative output artefacts that are data-based, such as Tik Tok, Coursera, Google Maps, Siri, and those related to the data-based features of IoT (Internet-of-Things) and other physical devices, equipment, machines, or infrastructure [3,4]. DBI benefits users with additional data-based utilities, such as analytics, search, recommendation, and Q&A, in the use process. DBI may result from an intuitive and human-social innovation process. In fact, DBI may benefit DDI, because it allows the generation of digital footprint data of users during their use process to feed and fuel a further data-driven innovation process [4].

DDI is also distinct from data-driven optimization (DDO) of operations, examples being using demand data and forecasts to inform procurement decisions for a supply chain operation, analyzing real-time traffic data to recommend nearest drivers in a ride hailing service, analyzing users' search behaviors to target online advertising, and analyzing stock market data to inform trading decisions. DDO requires well-defined objective functions, decision variables, and constraints, and often uses real-time data for specific variables to optimize the predefined objective functions, for greater operational efficiency, service delivery quality, and financial returns. In contrast, DDI is open-ended and aims to augment creativity to invent something new. DDI processes may discover new objectives and/or define new decision variables and create radically new values in the undefined whitespace.

While DDI, DDO, and DBI are all enabled by digitalization and computing, machine learning, and AI advances, they create different values for different agents in different types of actions or processes (Table 2). DDI addresses the uncertainty challenge facing innovators in creative processes and enhances the creativity for innovation. DDO optimizes the decisions of operators in the operational process with pre-defined operational objective functions. DBI increases the utility of products and services for users in the use process.

Table 2. Differentiating the Data-X Paradigms

	Data-Driven Innovation (DDI)	Data-Based Innovation (DBI)	Data-Driven Optimization (DDO)
Process	*Creative Process*	*Product/Service Use Process*	*Operational Process*
Agent	*Innovator*	*User*	*Operator*
Value	*Creativity*	*Utility*	*Optimization*

5. Evolution of Innovation Process Paradigms: From the Past to the Future

The innovation processes have evolved constantly over human history (Figure 2). In the 19th century, innovations came from individual creative geniuses, such as Thomas Edison, Alexander Bell, and Nikola Tesla. In much of the 20th century, well-organized processes in formal R&D labs and centers in large companies such as IBM and AT&T championed innovation. Since the 1970s, innovation ecosystems like Silicon Valley, where frequent and inexpensive knowledge flows across organizational boundaries, have emerged as the powerhouse of innovation.

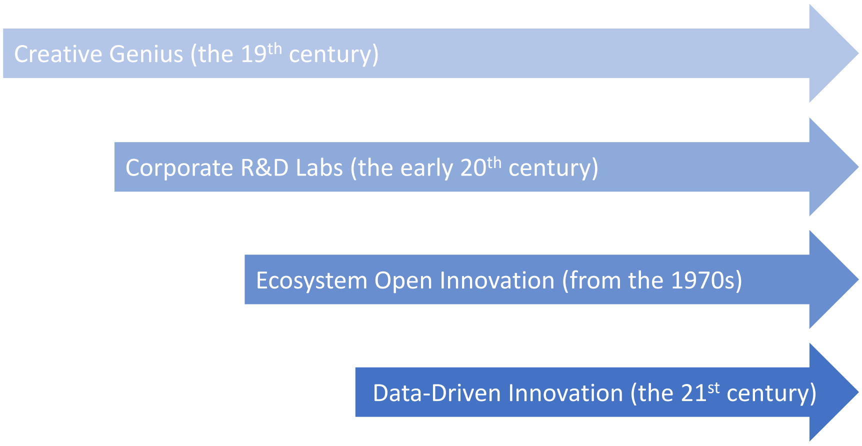

Figure 2. Evolution of Innovation Process Paradigms

Today, companies seek innovation opportunities and solution ideas via various proactive open innovation programs. They collaborate with university-based researchers, organize corporate venture labs jointly with external venture capitalists and entrepreneurs, and run open innovation contests, idea crowdsourcing campaigns, and hackathons to tap into collective and crowd intelligence. To date, the innovation processes have mainly relied on human intelligence (of either individuals, crowds, organizations, or ecosystems), with high serendipity.

As the society continually creates new knowledge and invent new technologies, we accumulate an expanding space of prior arts and knowledge, which can further benefit future efforts to innovate if they can be efficiently searched, retrieved, learned, and synthesized. Otherwise, the expanding space of prior arts may instead appear as knowledge burdens on future innovators, who would be required to learn and know a great deal more prior arts before they can innovate new products beyond the prior ones.

The growing knowledge burdens [22] will make the innovation process that solely relies on human intelligence less effective in the future. In contrast, data computation and rapidly advancing AI capabilities [23] can quickly and tirelessly learn an enormous knowledge from large unstructured datasets and transform or synthesize the learned knowledge to generate concepts of new products and services and automatically evaluate them. Artificial intelligence fueled with big data is driving us into the new "decade of technology intelligence [24]".

Therefore, the key enabler for DDI down the road will be the AI for creative tasks, namely, "Creative Artificial Intelligence (CAI)". CAI requires not only machine learning (of what exist) but machine creation (of new ideas). As we elaborated earlier, opportunity discovery, opportunity specification and idea evaluation can be augmented by machine learning (e.g., supervised, or unsupervised models), and idea generation can be augmented by machine creation (e.g., generative algorithms). With CAI, even a novice engineer, designer or manager can work creatively on tasks that would otherwise require extensive knowledge acquisition, creative thinking skills, and gut feeling.

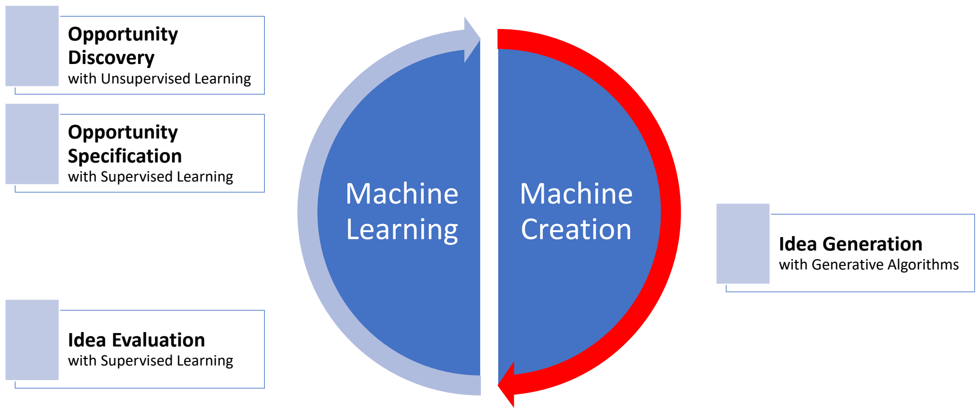

Figure 3. Creative AI requires both machine learning and machine creation

The future of innovation processes will be more data-driven and AI-empowered, while geniuses, R&D labs, open innovation activities and ecosystems will be continually important for innovation. However, data-driven innovation is still at the early stage of development and adoption [11,18]. A search in Google for "data-driven innovation" today finds few true data-driven innovation research and practice as we have defined here, but many in fact related to data-based innovation or data-driven optimization [1,2].

6. Embrace the Future toward Data-Driven Innovation

While companies and organizations around the world are actively applying machine learning and AI to make their operations, products, and services more data-driven [6], few have pursued nor succeeded in data-driven innovation, as we define here. Industrial firms tend to adopt data-driven decision making mainly for enhancing productivity [7], instead of creativity. There exist several impeding factors for the adoption of data-driven innovation by innovators and in organizations.

One bottleneck is the lack of readily available data-driven innovation methods, tools, and expert systems. Creative AI is under-developed in today's artificial intelligence R&D landscape, which is primarily focused on learning, classification, and pattern recognition tasks instead of creative ones. Companies should start with the off-the-shelf ML/AI algorithms and customize them to support creative tasks in the innovation process. Formal, fine-tuned, and standardized data-driven innovation methods, tools, expert systems, and workflows will emerge from continual trials and errors, heuristic learning, and capability building and scale in the future.

DDI requires data. To explore opportunities and generate new ideas for innovation, companies can creatively mine the public and free data sources, such as e-commerce sites, social media, open-source repositories (e.g., Github), patent and paper publication databases, and news archives. They can also mine and make use of those passively generated digital footprint data in their proprietary innovation activities, such as the records of prior failed experiments [25] or submissions or entries to their open innovation contests [26]. There are unbounded public or passively generated digital footprint data sources for innovators to mine, analyze and makes sense of for innovation. Despite additional investment required, companies may also redesign their workflows to purposefully generate and collect proprietary data streams to fuel their unique data-driven innovation needs.

DDI relies on people and organizations that can seamlessly integrate domain expertise, innovation process knowledge, and AI/data science skills. Traditionally trained innovators might not be capable of or comfortable with using ML/AI/data science to intelligentize the innovation process. The data scientists trained today are busy with applying their expertise to DDO and DBI, i.e., automating operations or increasing utility of user products and services, rather than the innovation process. For the long run, companies should collaborate with universities to educate and nurture future innovators with ML/AI/data science skills and future ML/AI/data science experts who aspire to make the innovation process more data-driven and intelligent. In the short term, strong leadership is needed to assemble DDI teams or retrain current specialists. An organizational culture that embraces data-driven innovation beyond the traditional innovation processes needs to be nurtured to support new data-driven innovation initiatives.

There exist many more social-technical factors [27] that may enable or condition the development and adoption of data-driven innovation by individual innovators or organizations. Also, the data-driven innovation processes may take different forms in different organizations and networks of innovation agents [5]. Systematic research into the factors for the adoption of DDI and the structures and modes of human-AI interactions in the innovation process will be desired to guide our journey toward the more data-driven and AI-empowered future of innovation processes.

The companies and organizations that start to experiment their own data-driven innovation processes and build relevant technological and organizational capabilities today may gain innovation advantages in the future. Meanwhile, the governments should also play a proactive role to facilitate the process, such as incentivizing or funding DDI-related talent and technological development, building infrastructure to enable public sector data accessibility to innovators and inter-organization data sharing. At the same time, policymakers should start to examine issues such as data privacy, security, ownership, civics, as well as the far-reaching DDI-induced economic, societal, and moral consequences and prepare policies and governance mechanisms [11,28,29].

We believe a clear and systematic understanding (as this article attempts to provide) of the essences of the data-driven innovation process, including what it entails, how it creates values and how it differs from other data-related paradigms, may guide the investments, capability building efforts as well as policy developments toward the future of data-driven innovation, to maximize its benefits and mitigate potential risks.

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