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Completed Research

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Abstract

The last decade has witnessed significant advances in artificial intelligence (AI), a process driven by new and more powerful algorithms, together with increases in both processing power and amounts of available data. As a result, many tools for adopting AI have become commodities for a broader mass of users. In this paper we focus on an emerging form of AI tools: AI service platforms. The objectives of this paper are to enhance understanding of these platforms' characteristics and, by providing a typology of AI service platforms, knowledge of their dynamics and evolution. Empirically it is based on a narrative review of literature on AI service platforms considering three dimensions: AI definitions, scope, and novelty. A major outcome is a typology of four AI service platforms, designated analytics, learning, conversational, and distributed platforms. In the presented analysis we discuss the current status and potential future development of these types. The findings increase conceptual clarity of AI service platforms and identifies patterns in their development over time. The latter include ongoing platform convergence leading to the types being increasingly intertwined, and a trend towards what we call 'lightweight AI', characterized by easy-to-use, low-code platforms.

Keywords

Artificial Intelligence, Machine Learning, AIaaS, AI service platforms, ML platforms

Introduction

With advances in techniques such as deep learning (Lecun et al., 2015) and increases in the development and availability of new tools for using artificial intelligence (AI), for both individuals and organizations, AI platforms seem to be here to stay. In this paper, we argue that understanding the nature and development of these platforms is important for information systems (IS) research. In line with Rai et al. (2019), we focus on next-generation digital platforms, stemming from AI technologies. Previous literature has presented AI typologies based on technology or functions (Benbya et al., 2020). However, a new breed of AI systems called 'AI as a service' (AIaaS) platforms, hereafter 'AI service platforms' (Lins et al., 2021; Geske et al., 2021), are becoming common, partly due to low adoption thresholds. Thus, we recognize a need to describe characteristics of these platforms in more detail. Lins et al., (2021) define AIaaS platforms as "cloud-based systems providing on-demand services to organizations and individuals to deploy, develop, train and manage AI models". The objective of these platforms is to make AI accessible and affordable for organizations that lack the scale or technological competence to exploit other kinds of systems. Moreover, AI service platforms can guide users through the process of developing and deploying AI models, without needing to learn complex algorithms. Since these services are often cloud-based, they also eliminate concerns regarding installation, maintenance and similar management problems. Large tech companies such as Amazon, Google, IBM and Microsoft started to offer AI capabilities as services in the mid-2010s, and other smaller companies soon followed their lead, resulting in a plethora of available AI service solutions (AML Team 2016, Bhattacharjee et al., 2017).

Recently, IS researchers have started to show interest in organizational factors that may influence firms' use of AI service platforms (see e.g. Zapadka et al., 2020, Pandl et al., 2021). As argued by Lins et al., (2021), the use of cloud technology in AI solutions enables organizations to access ubiquitous, convenient, on-demand resources that may be rapidly provisioned. However, as with AI in general, there is a lack of conceptualizations of AI service platforms in literature and practice, with a few emerging exceptions (see e.g. Geske et al., 2021).

There are three main motivations for refining both the conceptualization of both AI in general and specific types of tools, such as AI service platforms. First, to make IS a reference discipline for AI, as proposed by (Ågerfalk, 2020), current knowledge and understanding must be synthesized. Second, as explained by Collins et al. (2021), there is limited IS research on AI tools despite previous researchers calling for more attention to technological artifacts in IS research (Orlikowski and Iacono, 2001) and what these artifacts, or things, 'do' (Verbeek, 2005). Finally, improving conceptual clarity has practical benefits, as it can help to improve managerial decision-making regarding choices and uses of AI services. Against this backdrop, the objectives of this paper are to enhance understanding of these platforms' characteristics and, by providing a typology of AI service platforms, knowledge of their dynamics and evolution.

The rest of this paper is structured as follows: in the following section, we present a conceptual background with three dimensions: AI definitions, scope, and novelty. After that, we present methodological considerations of the literature review. Finally, we present the findings, followed by discussion and conclusions.

Conceptual Background

As noted by Lins et al., (2021), the research on AI service platforms is scattered and combines terminologies from several disciplines, for example 'analytics as a service' and 'machine learning (or deep learning) as a service'. Hence, to focus on AI service platforms it is necessary to borrow concepts from related research areas and integrate them with recent understandings, definitions, taxonomies and typologies of AI. Although the definition of AI varies in previous studies, some attempts have been made to summarize common definitions. While the frontier of what defines AI is constantly shifting (Berente et al., 2021), a commonly used definition in IS research according to Collins et al., (2021) comes from Russel and Norvig (2013). These authors proposed four categories of AI, as described below.

- Systems that think like humans. These systems can automate activities that we associate with human thinking, such as decision-making, problem-solving, and learning.
- Systems that act like humans. These systems perform functions that require intelligence when performed by people. The study and development of these systems involves identification of ways to enable machines to do things that (at the moment) people can do better.
- Systems that think rationally. These systems are capable of computations that enable them to perceive, reason and act.
- Systems that act rationally. These systems' purpose is to emulate and automate intelligent behavior through computational processes.

Another way of distinguishing between different types of AI is presented by Makarius et al., (2020), based on notions of novelty (low, moderate or high) and scope (content-changing or incremental AI, and context-changing or radical AI). Content-changing here refers to changes in a narrow task domain surrounding the associated system while context-changing refers to changes associated with AI more broadly, for example across value chains or ecosystems. Combination of the three novelty categories and two scope categories results in six 'types' of AI with associated human-AI relationships and human roles (Table 1).

Novelty / Scope	Content-changing	Context-changing
High novelty	Autonomous AI characterized by a high degree of independence, where humans keep the AI in check (e.g., autonomous vehicles).	Superintelligent AI enabled by a singularity (e.g. an intelligence explosion). Humans aim to comprehend the AI.
Medium novelty	AI that augments humans in collaborative relationships (e.g. robots in surgery).	AI that enables changes in its environment, acting in symbiotic relationships through which content is co-created together with humans (e.g. deep learning).

Low novelty	AI that automates functions through substituting humans (e.g. with decision support systems or automated online assistants). Humans act as controllers.	AI that amplifies functions, for example by making predictions. Humans have a supplementary role to the AI, acting as conductors.

Table 1. AI types (adopted from Makarius et al., (2020)

Low novelty AI may be content-changing by automating narrow tasks to substitute human labor, while AI systems that learn and make accurate predictions from data can alter contexts by amplifying and refining firms' capacities at several levels. Humans' roles shift between acting as controllers in the automation, and supplementary conductors to the AI systems in context-changing scenarios. As the novelty of AI increases, machines and humans are becoming increasingly intertwined as collaborators in complementary relationships in medium novelty implementations. In context-changing scenarios, which involves learning processes such as deep learning, organizations and industries may be fundamentally altered as humans and machines co-create unique content. At the highest level of this framework, sophisticated applications (such as facial recognition) in narrow areas characterize this type. The role of humans is to keep these autonomous systems (such as self-driving cars) in check as 'moral guardians'. The final type here encompasses high novelty and context-changing systems, which Makarius et al., (2020) refer to as superintelligent, limitless 'authentic AI'. These systems think, act and learn like humans, or can surpass them. They do not require human input or supervision, and while the relationship between humans and machines in this type is speculative at this point, the sociotechnical capital they generate might be limited due to the 'singularity' associated with the superintelligence (Boström, 2017). Humans' role is to 'comprehend' machines of this type. As noted by Makarius et al., (2020), the six types are ideal configurations and in practice there may be hybrid forms of AI types as well as human-machine relationships.

While useful, these insights from previous literature reveal a paucity of knowledge regarding types of AI that have been developed, or may emerge, and both the challenges and enablers associated with each type. Thus, the major broad aim of our narrative literature review was to acquire better understanding of the nature of these emergent phenomena.

Materials and Methods

This paper is based on a narrative review (Green et al., 2006) of literature on AI service platforms. As the literature on AI is heterogeneous and spans several disciplines, we considered material from various sources during the review, while retaining scientific rigor in the sampling.

After formulating the objectives, as outlined in the introduction, we commenced a search for relevant literature. Our aim was not to overview the literature exhaustively, covering all papers that have been written on AI service platforms. As argued above, the material's heterogeneity prevents such approaches, for example by accessing all relevant papers using a single or small group of search strings of keywords. Such an approach would exclude several important key papers that may be highly informative about how AI platforms work. Instead, we applied the principle that a research object is "entangled in a dynamic network of ideas and concepts that has no defined boundaries" and the "collection of relevant literature is always partial" (Schultze, 2015), so throughout the process we did not treat the literature as bounded and stable territory (MacLure, 2005).

To identify literature that includes descriptions and conceptualizations of AI service platforms, and thereby identify "Key texts regarded as representative of state of the art knowledge in a given area" (Schultze 2015 pp. 182), we used the AIS eLibrary and IS basket of eight journals as primary sources. This allowed us to generate a corpus with a solid foundation in IS research. However, since the literature on AI service platforms is fragmented in several fields, we also performed complementary searches of the Web of Science and SCOPUS databases. The searches involved use of Boolean operators with variants of "artificial intelligence" AND "platform*" and variants of "AI as a service": "AI as a service", AIaaS, "Machine learning as a service", MLaaS, "Deep learning as a service", DLaaS, and "Neural networks as a service" with and without hyphens. As the methodological approach entailed iterations between searching and analyzing material, additional papers were added to the review by complementary searches, and going back and forth using citations in the selected papers, as suggested by Webster and Watson (2002). The papers included in the review are designated P1-33 and are listed under the Further reading heading in the references section.

Analysis of the material was guided by the conceptual background presented in the previous section. Understanding in the analysis was generated through dialogue between the researchers and the texts in an iterative process (Boell and Cecez-Kecmanovic, 2014), in which 'types' of AI service platforms were constructed with respect to the mentioned definitions of AI, and both novelty and scope dimensions.

Results

Our analysis of the reviewed papers revealed four types of AI service platforms (analytics, learning, conversational, and distributed) together with their characteristics in terms of the three mentioned dimensions: AI definitions, novelty and scope. Each type is described in more detail, with references to the literature, in the following sections.

Analytics platforms

By introducing analytics as a service, smaller and medium organizations benefit by gaining insights from their data through automated forms of modelling, as shown for example by Kridel and Dolk (2013). Terms associated with analytics platforms are data analytics, data mining (Lomotey and Deters, 2014), and decision support systems (DSS) (Demirkan and Delen, 2013). These platforms have evolved from DSS, business intelligence systems, data warehousing and data management systems, to becoming increasingly intertwined with AI (Chen et al., 2012; Davenport, 2018). Schüritz et al., (2017) define analytics services as "services that employ a rich set of common analytics components and infrastructure, adjusted to fit industry-and company-specific requirements". They also note a distinction between 'basic' and 'advanced' analytics, and previous studies have distinguished several aspects or dimensions of analytics platforms (Demirkan and Helen, 2013; Hunke, 2019). As explained by Dremel et al. (2018) analytics providers vary in focus, functionalities and technologies. These authors propose a typology that includes five types: business intelligence, advanced reporting, ETL (extract, transform, load), advanced data management, and data mining. However, a common denominator of these systems is that they are expected to provide organizations with solid foundations for making decisions through analytics, and thus meet expectations for rational systems.

Demirkan and Delen (2013) refer to analytics services as means of generating insights from data from various sources, and turning a "general purpose analytical platform into a shared utility". Lismont et al., (2019) refer to analytics as a service as "a cloud-based service designed to support the entire data analytics process from data preparation to interpretation". Most analytics platforms include data-driven and cloud-based solutions ranging from data storage and preparation to model deployment and evaluation. These authors mention several potential benefits and challenges for organizations that want to start using analytics services, including advantages for inexperienced users.

Naous et al., (2017) argue that analytics as a service is a multifaceted concept associated with a range of applications arranged in cloud service layers, noting (p. 489) that ML and DL techniques are primarily used for predictive analytics to "discover explanatory and predictive patterns". Moreover, recent studies by Watson (2017) and Davenport (2018) suggest that analytics platforms are evolving from rule-based-systems as ML and DL models are increasingly deployed. Watson (2017) argues that the next generation of DSS will be increasingly intertwined with AI techniques, and as AI becomes more embedded it will equip them with advanced analytics capacities, as well as natural languages interfaces. Davenport (2018) describes the evolution of analytics platforms from a focus on business intelligence and data management that generated value through internal decision support to systems that increasingly incorporate AI and ML, especially for predictive functions (see also, Merkert et al., 2015).

Learning platforms

As argued by Griebel et al., (2013), advances in accessible tools for ML and DL provide opportunities for IS researchers to study specific practical uses of AI. Koppe and Schatz (2021) highlight the potential for cost-effective use of cloud-based ML services. They note that these services simplify use of AI technologies by supplying pre-trained neural networks as part of cloud services. These services often support the whole development process, from uploading data to model deployment, even with smaller data sets due to the use of transfer learning (for example, through pre-trained models such as BERT and EfficientNet). Elshawi et al., (2018) refer to a range of cloud ML services, such as IBM Watson and BigML. Pawar et al. (2021) describe ML services as "integrated and semiautomated web devices covering most facilities problems such as preprocessing information, design preparation, and design assessment with the further forecast. Application Program Interfaces (APIs) can bridge the outcomes of predictions with one's inner IT infrastructure."

Machine learning services involve integrated and semiautomated functions for preprocessing, designing and deploying models with an organization's IT infrastructure through use of APIs. These high-level services provide access to infrastructure and platforms. Pawar et al., (2021) identify the most common (cloud) technologies used for ML as a service as Google Cloud AI, Amazon, and Microsoft Azure. This type of service guides users' development and configuration of AI models in ML workflows (Lins et al., 2021). These workflows typically include a process ranging from uploading data, training and evaluating a ML model, and deploy it for integration with an organization's IT infrastructure via APIs. This, in turn, increases the effort expectancy of the user, since s/he is actively involved in working closely with training the AI, co-creating content through training and fine-tuning ML models. Here AI is expected to think and learn like a human, based on neural networks and DL.

Examples of these general-purpose ML and DL platforms are Peltarion, previously called Synapse, as mentioned by Aisa et al., (2008), and Google's AutoML. A trend here is that AI platforms are becoming general-use products, with a wide array of potential applications, and user-friendly 'lightweight' interfaces. In this context, scholars describe the need for AI platforms that are easy to use in several operational contexts to lower the threshold for non-experienced users. For example, Gao et al. (2021) argue that ML and DL provide efficient approaches for drug development, but the lack of code-free and user-friendly applications hinders domain experts' use of these kinds of tools. Examples of such user-friendly AI platforms include general learning platforms that utilize user-friendly graphical user interfaces, in combination with no-code, or low-code environments, as shown by Laverde-Saad et al., (2021).

Conversational platforms

The first AI system to process natural language input for communication purposes was ELIZA (Weizenbaum, 1966). During the last decade, chatbots such as Apple's Siri, Amazon's Alexa and Microsoft's Cortana have become commonplace features of our everyday technology (Dale, 2016). Conversational services share the common feature of a front-end interface, where the user can communicate with the AI through text or voice. Such types of AI service platforms generate value through anthropomorphism as they mimic human behavior (see Li and Suh, 2021), they have several names in the literature, including 'chatbots' and 'conversational AI systems' and they can enhance perceived user value by providing convenient access to data, leveraged through a human-like interface (acting like humans) (Schanke et al., 2021). Through the interface, users can interact with the AI by providing input in the form of queries and questions in a natural language and receive outputs in the form of answers in response.

Hepp (2020) highlights that many bots, or 'communicative robots' (artificial companions, social bots, work bots), are not necessarily intelligent; they may consist of simple scripts for the automatic generation of content. Thus, Hepp defines these bots as characterized by automation, a communicative purpose, embedding in a digital infrastructure, and a 'humanlike' user interface. Machiraju and Modi (2018) argue that, like analytics AI platforms, the development of conversational platforms is being increasingly driven by advances in ML. For example, Sjöström et al., (2018) developed a chatbot using the PandoraBots platform for use in higher education and recognized the technological feasibility of training it automatically, although they used supervised training to "align its behavior with institutional norms, and to ascertain quality of responses".

Distributed platforms

Distributed AI services are beginning to receive increasing attention in the literature, but mainly conceptual as the operational areas concerned, such as autonomous vehicles, are still immature. As described by Jöhnk et al., (2021), relevant technologies such as AI, the Internet of Things (IoT) and blockchain can be conceptualized as converging as they collectively provide foundations for diverse applications, such as energy systems, autonomous vehicles and intelligent warehousing. An obvious question to consider as increasing numbers of intelligent systems are constructed (particularly by Multi-Agent-System constructors, users and investigators) is how they will interact with each other (Stone et al., 2016).

The main characteristic of distributed platforms is a range of connected devices spanning several applications and systems. These platforms' distributed nature also makes them challenging to assign to a 'type' since the 'distribution' is described in many forms in the literature. They often form multi-agent ('smart') configurations in domains such as buildings and vehicles, where autonomous AI agents act and react in relation to each other. While some studies describe these systems in purely conceptual terms, they can potentially have relatively high novelty due to their autonomy and independency. Examples include collaborative systems that can work cooperatively with other systems, humans, IoT-enabled devices, such as vehicles and buildings, and may be interconnected to collect and share their sensory information (Stone et al., 2016). The availability of large data sets has made transportation an ideal domain for ML, but such applications require robust infrastructure and standardization of sensing and AI techniques. Once these challenges are overcome, advances in multi-agent coordination, collaboration, and planning can occur in systems that act rationally and autonomously. The combination of equipment that is being imbued with intelligence (Tschang and Mezquita, 2020), and increasing autonomy of AI, is generating new opportunities for firms, as well as risks related to the agency of the AI that must be addressed, as discussed for example by Sidorova and Rafiee (2019).

Janbi et al., (2020) conceptualize distributed AI as a service (DAIaaS) systems as having several layers where "the actual training and inference computations are divided into smaller concurrent, computations suited to the level and capacity of resources available with cloud, fog, and edgelayers." Examples of application domains include various ('smart') environments, such as airports. A common denominator of this type of AI platform is extension of the scale and scope of applicability. This enables distributed platforms to form multi-agent systems in, for example, industrial environments in the wake of Industry 4.0, in 'smart grid' electrical systems (see, for example, Ali and Choi, 2020), and 'smart buildings', where they form autonomous systems.

Discussion

The findings, as summarized in Table 2, reveal how four types of AI service platforms (analytics, learning, conversational, and distributed) differ in terms of AI definitions, novelty and scope. While reviewing the literature, we noted how analytics platforms are shifting from content-changing to context-changing forms through intensified use of ML and DL models, especially in predictive analytics platforms. Conversational platforms may be highly suitable for classic analytics functions and automation, but ML and DL capacities are also being incorporated in them, including natural language processing to enable conversational learning. Finally, distributed service platforms are an emerging type characterized by shifts in novelty and scope. They are conceptually described in the literature and thus more difficult to reduce to a type. As they consist of multiple agents, they may include features of the other types, including analytics functions, self-learning capacities, and conversational AI in 'smart' environments.

Type / AI definition	Novelty and scope	Examples of platforms	Example papers
Analytics: Systems that think rationally and act according to rules and formal procedures. (e.g. decision support systems and rule-based systems).	Low level of novelty. Content-changing through automation (e.g. DSS). | Context-changing through amplification (e.g. predictive analytics). Humans act as controllers or conductors.	Civis Analytics, Kognito Analytical Platform, Informatica	P3, P5, P6, P7, P11, P15, P16, P17, P18, P19, P22, P24
Learning: Systems that think like humans, through neural networks (machine learning and deep learning as a service).	Medium level of novelty. Context-changing through alteration (e.g. deep learning). Humans act as co-creators.	Amazon Sage Maker, BigML, Google Cloud AI, IBM Watson,	P1, P8, P9, P14, P20, P26, P29, P33

		Microsoft Azure AI, Peltarion	
Conversational: Systems that act like humans through an interactive interface (e.g. conversational agents, chatbots, voice bots, voice assistants).	Low level of novelty: Content-changing through automation (e.g. substitution of humans by chatbots). Humans act as controllers.	IBM Watson chatbot, Azure Bot Service, PandoraBots	P4, P10, P21, P23, P25, P27, P30
Distributed: Systems that act rationally in multi-actor environments ('smart', multi-agent systems and EDGE computing).	High level of novelty: Content-changing through autonomous systems (e.g. 'smart systems'). Autonomous, independent systems kept in check by humans.	(not mature enough for full platform creation)	P2, P12, P13, P28, P31, P32

Table 2. AI service platforms typology

The results also include important findings about how scholars depict anticipated trends in these platforms' development. The next part of this discussion outlines these trends and their expected effects on the dynamic interplay between the types.

Types of AI platforms and platform convergence

Although we propose a typology of four types of AI service platforms (analytics, learning, conversational, and distributed), we also acknowledge that the boundaries between these types are not always distinct in the literature. Analytics platforms have evolved from DSS, data warehousing and big data analytics systems and are becoming increasingly intertwined with learning platforms, through the use of ML and DL for predictive analytics. These learning services represent a common 'archetype' of platforms, according to our study, as they provide a range of pre-trained models (such as BERT and EfficientNet) on cloud platforms. Moreover, conversational platforms may provide analytics functions for the hosting organization and/or natural language processing ML/DL capacities to generate more relevant responses to end users through human-like interfaces. For example, the comprehensive IBM Watson AI suite is bundled with the 'Watson Assistant' conversational interface. Hence, we identify a trend in the development of AI platforms towards mergers of the types outlined in this paper, which we refer to as platform convergence, as the boundaries between them are becoming increasingly blurred. This development is in line with earlier literature where the merge of different types of intelligent systems is described (Turban and Watkins, 1986).

Finally, we argue that distributed AI services may have features of all of the other three types, supplying the hosting organization(s) with analytics and learning functions, but also various inputs, including conversational inputs from users in 'smart' environments. As argued by Tschang and Mezquita (2020), the combination of AI with analytics, technologies such as cloud computing and IoT, and digital transformation founded on platformization enables massive competitive advantages over traditional modes of business organization due to the amplification of scale and scope. Hence, although AI has been separated into sub-fields, and typologies such as that proposed here have been formulated, it should also be recognized that synthesizing intelligence requires the integration of diverse ideas. Hence, the evolution of AI includes both separation and convergence of ideas over time. Drawing upon this convergence, we observe a development in AI from specific uses /domains to a set of generic platforms. As AI architecture is becoming standardized and includes general pre-trained models that may be adapted for many different uses, we argue that the future of AI platform services will be increasingly characterized as generic, for use in several domains.

AI platform evolution: Towards 'lightweight AI'

As we see the archetypal 'learning' platforms becoming important facilitators that promote interactions between actors that previously would not or could not engage with each other, the 'generic' AI service platforms mentioned above could potentially increase AI's accessibility to more actors, and thus promote its democratization. As AI spreads into more domains and involves increasingly heterogeneous users AI platforms are becoming increasingly easy to use. Accordingly, several scholars have highlighted the importance of creating systems that can be used not only by data experts, but also by professionals in diverse domains (Koppe and Schatz, 2021; Pawar et al., 2021; Laverde-Saad et al., 2021).

Broader societal consequences depend on the population having access to the tools for realizing them. As a range of 'no-code' solutions become commonalities, users may train ML and DL models with little or no prior coding experience (see, for example, Laverde-Saad et al., 2021). We argue that that these new platforms can be referred to as 'lightweight' (c.f. Bygstad, 2017) forms of AI, as they reduce the gap between data experts and more novice users, and augmentation may serve a wider range of users, including non-experts that interact with intelligent systems. Under these circumstances, domain expertise becomes crucial for achieving complex AI objectives, while detailed understanding of the designed algorithm, and the AI platform per se, becomes less important. As the ecosystems of users and functions surrounding these AI service platforms extend, we recognize that our notion of AI 'types' will also be challenged as they increasingly become parts of platform suites and multi-faceted systems. However, typologies still provide important demarcations that decision makers in organization need to consider while they plan their AI implementations.

Conclusion

The objectives of this study were to generate a typology of AI service platforms and understanding of their evolution and dynamics. The outcome is a typology including four types of AI service platforms, designated analytics, learning, conversational, and distributed platforms. Our findings provide insights regarding these platforms' correspondence with different definitions of AI, and in their scope and novelty. They also illuminate the evolution of AI platforms, by highlighting trends towards AI becoming increasingly lightweight, accessible and broadly used. Our study contributes to the literature by refinement of key concepts related to AI service platforms and positioning these emerging platforms within previous definitions of AI.

Based on our findings, we identify several opportunities for further research. First, following developments of various AI types, and both their distinctions and convergence, will generate important knowledge on the nature and characteristics of AI. Second, exploring the use of 'lightweight' AI service platforms, characterized by easy-to-use graphical interfaces, pre-trained models, and no-code or low-code solutions, in various domains will provide rich insights into actual adoption and managerial practices associated with them.

This research was not without limitations. In line with Dremel et al. (2018), we recognize that the market of AI service platforms is constantly evolving, which reduces the validity of taxonomies and typologies over time. However, they constitute important references that map out the current landscape, and we encourage scholars to further follow the trajectory of these platforms.

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