GATEWAYS TO ARTIFICIAL INTELLIGENCE: DEVELOPING A TAXONOMY FOR AI SERVICE PLATFORMS

Research Paper

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Abstract

Artificial Intelligence (AI) carries the potential to drive innovation in many parts of today's business environment. Instead of building AI capabilities in-house, some organizations turn towards an emergent phenomenon: AI service platforms. However, as a novel concept in both research and practice, a systematic characterization of AI service platforms is missing. To address this gap, we define the concept of AI service platforms and develop a comprehensive taxonomy. Therefore, we rely on existing literature, 14 expert interviews, and a sample of 31 AI service platforms. Our contribution is threefold: First, our taxonomy systematically structures essential properties of AI service platforms, guiding future research and management practice. Second, we derive three generic motives of AI service platforms. Third, we contribute to the literature by critically discussing to what extent AI service platforms fit into the existing academic discourse on digital platforms and elaborate on future research directions.

Keywords: AI Service Platform, Digital Platform, Artificial Intelligence, Taxonomy.

1 Introduction

Fostering developments in new products, services, and business models, Artificial Intelligence (AI) is experiencing attention in research and practice. AI applications are diverse and involve different technological approaches. Examples range from classification in medical diagnosis (Hofmann et al., 2019) to the generation of music (Hofmann et al., 2021). Today, AI has moved from the theoretical realm to the global marketplace. Amongst others, the maturing of machine learning (ML), the availability of data, and adequate computing power have fueled the rise of AI (Jordan and Mitchell, 2015). Despite AI's promised potential, companies have not yet widely adopted AI. Lorica and Paco (2019) state that only 27 percent of the observed companies are already deploying AI, while another 54 percent are currently evaluating the technology in the short term. Although an increasing number of companies aim to incorporate AI, in-house development is difficult due to insufficient know-how. Accordingly, companies focus on obtaining AI capabilities as external services and begin to acquire AI capabilities on platforms. Thus, AI platforms may contribute to an organization's AI readiness (Jöhnk et al., 2021). The coincidence of the need to seize the AI potential and develop appropriate resources and capabilities motivates service providers to create new AI-related services. AI platforms are a means to offer such AI-related services. Rai et al. (2019, p. iii) refer to AI platforms as "next-generation digital platforms, arising from the application of artificial intelligence (AI) technologies." In Gartner's 2019 Hype Cycle for Emerging Technologies, AI platforms are almost at the peak of their hype phase and expecting a broad adoption within the next five to ten years (Gartner Inc., 2019). To adopt an AI platform's services, organizations need to evaluate the landscape of AI platforms.

Academic literature has so far scarcely investigated the phenomenon of AI platforms. Previous research mainly concentrates on technical or application-specific aspects. For example, Ribeiro et al. (2015) propose a technical architecture for digital platforms using ML. Tafti et al. (2017) already offer a brief overview of AI platforms but do not provide a general systematization. Rai et al. (2019) describe examples of major AI platforms as ML model libraries and frameworks, which are accessible open-source, as AI-powered services available through Application Programming Interfaces (APIs), as drag-and-drop environments to run custom, or as pre-trained ML models available for use case-specific deployment. Although Rai et al. (2019) use the term AI-powered services, the authors only refer to AI platforms as technical representations of the inherent AI service. However, to the best of our knowledge, no attempts have been made to provide an overview over platforms providing discrete AI services – so-called AI service platforms. It remains unclear what properties characterize AI service platforms available on the market and how we can conceptualize them along with existing theory. On the one hand, a structuring artifact characterizing AI service platforms is necessary to organize and guide decisions in the selection and (organizational) integration of AI services. On the other hand, a fuzzy characterization of AI service platforms restricts the comparability and referenceability of future research. In this endeavor, we pose the following research question:

Which essential properties characterize the multitude of AI service platforms in practice?

To answer our research question, we developed a taxonomy following the established guidelines of Nickerson et al. (2013). By applying conceptual-to-empirical and empirical-to-conceptual iterations, we relied on the existing literature, the researcher's knowledge and experience, and a sample of available AI service platforms. We further extended primary data by conducting 14 semi-structured expert interviews. These interviews allowed us to induce a practitioner's perspective into our taxonomy. Hereafter, we applied our taxonomy to 31 identified AI service platforms and discuss our findings.

Our contribution to theory and practice in this context is threefold. By developing and applying our taxonomy, we provide a structured overview and systematization of AI service platforms, aiding a common understanding. We derive three generic motives of AI service platforms from our research. We also contribute to the literature by critically discussing how AI service platforms fit into the existing academic discourse on digital platforms and elaborate future research directions.

2 Foundations

Platforms have transformed many industries, such as retail, ride-hailing, and hospitality services (Hagiu and Wright, 2015). Digital platforms, in particular, enable large-scale access to resources, which would not have been accessible at the same scale before (Constantinides et al., 2018). In doing so, organizations create value by exploiting network effects through platformization (Setia et al., 2020). Therefore, both incumbents and start-ups across all industries adapt their business models to the platform paradigm. To remain competitive, firms increasingly adopt platform thinking in their strategic considerations (Constantinides et al., 2018). However, research still lacks insights on what types of digital platforms organizations adopt in particular (Reuver et al., 2018).

The literature on digital platforms lacks a comprehensive and universally accepted definition. Over the past decades, the understanding of digital platforms evolved significantly, resulting in three different streams within IS research to be distinguished (e.g., Hein et al., 2020). From a technical point of view, digital platforms comprise “a modular architecture consisting of a stable core component and many changing peripheral components” (Rolland et al., 2018, p. 421). This literature stream considers the technical structure and capabilities enabled by digital platforms (Gawer, 2014). However, the economic perspective mainly views digital platforms in terms of value co-creation and capture (Gawer, 2014; Rolland et al., 2018), typically incorporating perspectives from the economics literature. This stream of literature regards platforms as connecting buyers and sellers on a marketplace (Rochet and Tirole, 2003) and, therefore, often focuses on the transactions between actors facilitated by platforms. Third-party contributors are thus an integral and defining element of (digital) platforms in this view. A third organizational perspective describes digital platforms as socio-technical phenomena encompassing technical components that enable business networks (Reuver et al., 2018; Blaschke et al., 2019). In summary, research has widely discussed the concept of digital platforms, but its definition can differ significantly depending on the point of view taken. Nowadays, the practical and theoretical view on platforms is often high-tech-business and IT-driven (Gawer and Cusumano, 2014). In practice, the term ’platform’ appears to be used inflationary. Among others, organizations tend to call their offerings a platform for marketing purposes (Hagiu, 2009), although they do not offer the characteristics typically proposed in the various literature-based definitions.

As a new phenomenon, AI platforms integrate the concepts of digital platforms and AI. According to Nilsson (2010, p. 13), AI “is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment.” Correspondingly, AI refers to a field of computer science dealing with the simulation of intelligent behavior (Russell and Norvig, 2016). AI services are – regardless of their specific technological implementation – capable of performing cognitive functions (Hofmann et al., 2020; Rai et al., 2019). Currently, ML is one of the most relevant technologies to approach AI, advancing capabilities in, among others, natural language processing or computer vision (Jordan and Mitchell, 2015; LeCun et al., 2015). In the light of multiple digital platform definitions and the confusion through marketing efforts, we found that the concept of AI platforms lacks a concise and unambiguous definition in the academic discourse. From a technically oriented perspective, Rai et al. (2019) describe examples of major AI platforms. These include ML model libraries and frameworks, accessible open-source, AI-powered services available through APIs, drag-and-drop environments to run custom ML models, and pre-trained ML models available for use case-specific deployment. The authors highlight that AI enables new possibilities for humans to perform tasks on digital platforms as well as for the governance of digital platforms themselves. While their description covers many AI platform services, we found it not exhaustive and not in line with traditional definitions of digital platforms. To capture their nature observed in the market and to guide the process of selecting a suitable sample for our taxonomy development, we sought to define AI service platforms for our research.

Therefore, restricting the definition of AI platforms to digital platforms from a technical perspective would not account for the variety of artifacts in the real world, which, for example, included marketplaces for ML models without a shared codebase at the core of the platform. To solve the ambiguity of the digital platform characterization, we adopted the platform concept by Gawer (2014), as it provides an integrative perspective bridging the economic, technical as well as organizational views on digital platforms from different research streams: *“Technological platforms can be usefully seen as evolving organizations or meta-organizations that: (1) federate and coordinate constitutive agents who can innovate and compete; (2) create value by generating and harnessing economies of scope in supply or/and in demand; and (3) entail a technological architecture that is modular and composed of a core and a periphery”* (Gawer, 2014, p. 1240). This definition integrates both the technological architecture of a platform and the role of an intermediary, which applies if a platform coordinates more than one agent within or across firms. Furthermore, it captures a platform’s intent to be more cost-efficient than rival solutions by sharing core functionality. Accordingly, we understand AI service platforms as a platform that enables the provisioning and exchange of AI services between two or more agents.

3 Research Method

To structure and analyze the phenomenon of AI service platforms, we developed a taxonomy following the guidelines of Nickerson et al. (2013). The term taxonomy refers to a form of classification in which one derives a system of groupings empirically or conceptually (Nickerson et al., 2013). In the IS discipline, various papers have already applied taxonomies successfully to structure nascent research fields (e.g., Jöhnk et al., 2017; Püschel et al., 2016; Lösser et al., 2019). For this reason, we consider it appropriate to develop a taxonomy for grasping the still elusive phenomenon of AI service platforms. IS research benefits from organizing a complex and unspecific concept in a taxonomy (Grimshaw, 1992) to obtain a foundation for a future, common understanding of the AI service platform concept.

The iterative method proposed by Nickerson et al. (2013) starts with defining an encompassing meta-characteristic that directs the creation of the taxonomy's characteristics and dimensions. The dimensions aggregate characteristics into groups. We follow this approach to capture all possible combinations in an efficient and well-arranged manner. By referring each characteristic to the meta-characteristic, we ensure that the final taxonomy aligns with the taxonomy's purpose. To specify a meta-characteristic, it is useful to define the target user(s) and the taxonomy's intended purpose in a first step (Nickerson et al., 2013). Furthermore, it is important to determine ending conditions for taxonomy development, which ensure the formal correctness of the taxonomy and its usability. Then, an iterative development process takes place. Each iteration follows either a conceptual-to-empirical or an empirical-to-conceptual approach, depending on data availability and the researcher's prior state of knowledge. While the conceptual-to-empirical approach relies on existing literature and the researcher's knowledge and experience, the empirical-to-conceptual approach analyzes a sample of available objects and extracts shared characteristics of them. The iterative development process terminates when the ending conditions are met (Nickerson et al., 2013).

For our meta-characteristic, we defined the following target group: scholars and practitioners aiming to understand the various concepts of platform-based AI services for making informed decisions. Therefore, our meta-characteristic is "*essential properties characterizing of AI service platforms in practice*". As ending conditions, we rely on both the objective and subjective ending conditions introduced in Nickerson et al. (2013). The objective ending conditions are defined as follows: First, the analyzed sample of objects must be relevant. Second, during the last iteration, objects were neither split nor merged and no new characteristics or dimensions were added, split, or merged. Third, every dimension, characteristic, and cell must be unique. The subjective ending conditions include taxonomy's robustness, conciseness, comprehensiveness, explainability, and extensibility (Nickerson et al., 2013).

For our first iteration, we chose the empirical-to-conceptual approach for two reasons. First, conceptual knowledge about AI platforms as an emerging phenomenon is still very limited (Mwilu et al., 2015; Williams et al., 2008). Second, the World Wide Web contains information about a sufficient number of AI service platforms. Conducting an online search, we set out searching for AI service platforms relying on Google search and the website of PAT Research, a B2B platform providing research and reviews for enterprise software and services (PAT Research, 2019). Further, we drew on a sample of AI service platforms from the online database for software G2 (G2 Crowd Inc., 2019) to extend our initial sample. In doing so, we deliberately decided to exclude software libraries (e.g., Keras) from our research because such libraries solely focus on the collection of 'code snippets' rather than providing marketable and salable services in the narrow sense. The snippets themselves do not add further functionality to the platform but instead require deployment on a different infrastructure, which the customer must set up himself or obtain from a cloud provider at additional cost. Furthermore, such libraries do not share a similar core to enable economies of scope. We, therefore, concluded that software libraries do not comply with the notion of technological platforms. In total, we identified 31 AI service platforms offered by incumbent firms and start-ups. In doing so, we identified the following AI platforms: Afresh, Algorithmia AI Layer, Amazon Sage Maker, Artivatic, AWS Marketplace, Ayasdi, BigML, Civis Analytics, CreateML, Data Robot, Dataiku, Deep Cognition, Domino Datalab, Figure Eight, Fritz.ai, Google Cloud

AI Platform, IBM Watson, Inbenta, InfoSys Nia, KAI, Meya, MLJAR, MS Azure AI, Nuance Marketplace, Peltarion, Playment, Rainbird, Receptiviti, Salesforce Einstein, Uptake, and WorkFusion. For the first iteration, we drew a random sample of 15 AI service platforms.

To refine our initial taxonomy, we followed a conceptual-to-empirical approach in our next iteration. Therefore, we contextualized available conceptual knowledge drawing on the body of literature. As a result, we added, adapted, and combined several dimensions and characteristics of our taxonomy and conducted a second empirical-to-conceptual iteration using an extended sample of artifacts. After an unsatisfactory evaluation of the ending conditions, we conducted semi-structured expert interviews to gain new primary data (Myers and Newman, 2007; Jöhnk et al., 2017). Our interviews impacted the development of the taxonomy by indicating shortcomings in some dimensions (e.g., ambiguous wording or missing characteristics) and opportunities for improvement (e.g., the presentation of the taxonomy). Besides adjusting the taxonomy, the gained insights enabled us to validate the taxonomy by experts from practice, thereby ensuring practical relevance. We provide details about the interviewed experts in Table 1. The interview guideline included both open and closed questions (Myers and Newman, 2007) and consisted of three main sections: (1) introductory questions on the expert's background regarding AI platforms, (2) general statements on AI platforms, and (3) a discussion of the existing taxonomy and general questions on improving the overall taxonomy and missing aspects. The interviews lasted between 20 and 63 minutes. We recorded all interviews allowing for systematic analysis. In doing so, we avoided restricting our analysis to our experiences from previous development cycles. To satisfy our meta-characteristic and integrate both supply and demand perspectives, we drew experts from organizations either applying or offering AI platforms in practice. Based on new primary data, we were able to solve the mature issues of our taxonomy.

Expert	Industry	Position	Total years of experience	Interview length (in minutes)
01	Mechanical Engineering	Managing Director	15-20	63:49
02	Automotive	IT Project Manager	<5	28:23
03	Entertainment	Head of AI Platform Services	5-10	33:09
04	Academia	Professor of Computer Science	15-20	44:07
05	Semiconductor	Trainee	<5	23:45
06	Automotive	Supply Chain Lead	<5	20:17
07	IT	Founder, CEO	10-15	19:02
08	IT	AI System Engineer	>10	26:57
09	IT Consulting	Managing Consultant	5-10	24:07
10	Semiconductor	Senior Manager	>25	60:00
11	IT	CO-Founder AI-Startup	<5	28:42
12	Finance	Product Owner AI Research	15-20	46:19
13	IT (AI Platform)	Founder, CEO	<5	55:16
14	IT (AI Platform)	Manager Customer Engineering	>10	39:52

Table 1. Overview of experts.

To match our taxonomy with existing AI service platforms, we conducted another empirical-to-conceptual iteration that allowed us to classify our complete sample of AI service platforms. After slight adjustments resulting from the subsequent iteration, we collected and incorporated scholar feedback from taxonomy experts. After that, another conceptual-to-empirical iteration allowed us to verify our taxonomy in the light of the changes made. There was no longer any need to change the taxonomy in the last iteration since our taxonomy meets the ending conditions. For transparency, we further provide supplementary material regarding our interview guideline and taxonomy application in Geske et al. (2021).

4 Taxonomy for AI Service Platforms

Within this section, we present our final taxonomy and apply real-world AI platforms to it. Throughout these following steps, 'customer' refers to an organization that considers utilizing an AI platform.

4.1 Introducing the final taxonomy

Figure 1 depicts our final taxonomy, which consists of three layers. The customer context describes the contextual fit between the customer and the AI service platform. *AI service platforms' offering* encompasses the functional fit between the customer's requirements and the AI service platform's technological offerings. Third-party integration describes the access and interaction between the customer and third parties contributing to the platform. The taxonomy's layers and dimensions integrate into Gawer's (2014) classification system of technological platforms.

<table>
<tr><th></th><th>Dimension</th><th colspan="20">Characteristics</th></tr>
<tr><td rowspan="3">Customer context</td><td>Industry focus</td><td colspan="10">industry-specific</td><td colspan="10">industry-unspecific</td></tr>
<tr><td>Activity focus</td><td colspan="10">activity-specific</td><td colspan="10">activity-unspecific</td></tr>
<tr><td>Platform use</td><td colspan="5">continuous</td><td colspan="5">continuous and on-demand</td><td colspan="5">on-demand</td><td colspan="5">none</td></tr>
<tr><td rowspan="7">AI service platform' s offering</td><td rowspan="2">AI service model</td><td colspan="5">application deployment service</td><td colspan="5">application development and deployment service</td><td colspan="5">hybrid service</td><td colspan="5">ready-to-use service</td></tr>
<tr><td colspan="20">none</td></tr>
<tr><td>Complementary services</td><td colspan="10">yes</td><td colspan="10">no</td></tr>
<tr><td>Complementary resources</td><td colspan="10">yes</td><td colspan="10">no</td></tr>
<tr><td>Pricing model</td><td colspan="4">one-off payment</td><td colspan="4">regularly based on variable rates</td><td colspan="4">regularly based on fixed rates</td><td colspan="4">freemium</td><td colspan="4">free of charge</td></tr>
<tr><td>Code-based interaction</td><td colspan="10">yes</td><td colspan="10">no</td></tr>
<tr><td>Graphical interface</td><td colspan="5">click through</td><td colspan="5">click through and drag and drop</td><td colspan="5">drag and drop</td><td colspan="5">none</td></tr>
<tr><td rowspan="2">Third-party integration</td><td>Integrated complementor</td><td colspan="5">selected complementors</td><td colspan="5">selected complementors and crowd</td><td colspan="5">crowd</td><td colspan="5">none</td></tr>
<tr><td>Integrated complementor offering</td><td colspan="5">resource</td><td colspan="5">resource and service</td><td colspan="5">service</td><td colspan="5">none</td></tr>
</table>

Figure 1. A taxonomy of AI service platforms.

4.1.1 Customer context

The layer *customer context* includes the dimensions *industry focus*, *activity focus*, and *platform use* to locate and describe the area of application as well as to assess the AI service platform's specialization from a customer's perspective. In this way, the taxonomy characterizes the context-specificity of accessible, innovative capabilities and their use (Gawer, 2014).

The dimension *industry focus* distinguishes between industry-unspecific to industry-specific offerings. The trend towards industry-specific offerings can be observed for cloud services, as offerings customized to the needs of a specific industry can better address concerns about security, privacy, control, and interoperability of data (James and Chung, 2015). With this dimension, we can distinguish AI service platforms based on their integration of industry-specific knowledge into the AI service platform's offerings. Industry-specific offerings are designed for a narrow use case and, therefore, address the industry-specific challenges of applying AI. For example, *KAI* provides a banking-specific conversational AI solution that interacts with banking customers. By integrating banking-specific domain knowledge (e.g., financial terminology), *KAI* can offer a practically ready-to-use AI service. As another example, *Uptake* incorporates industrial asset failure signatures across industries. While not just focusing on a single industry, *Uptake* integrates industry knowledge. Therefore, the dimension industry focus can capture different levels of abstraction. In contrast, *Algorithmia* provides, amongst others, development and training as well as a deployment environment without a specific industry focus. Similarly, the data-annotation platform *Figure Eight* offers an industry-unspecific service to annotate data.

The dimension *activity focus* assesses whether the AI service platform focuses on a certain organizational activity or whether it provides an activity-agnostic service. That could include, among others, logistics, operations, or sales. Considering the effect on the end-product offered by the AI service platform's customer, the dimension *activity focus* allows distinguishing between direct (e.g., providing service as a part of the end-product) and indirect (e.g., development environment) effects. The activity focus is not only relevant from a knowledge specialization perspective but also from a sourcing perspective. We, therefore, motivate analyzing business units affected by AI service platforms' offerings in line with (IT) outsourcing literature (e.g., Cullen et al., 2005). In particular, mature AI services such as the conversational AI service offered by *KAI* may target a specific activity and therefore become the subject of an outsourcing endeavor. As characteristics for the dimension *activity focus*, we draw on activity-specific characteristics and activity-unspecific characteristics. The activity focus may comprise, among others, logistics, operations, marketing and sales, customer service, or human resource management. An example of a platform targeting a specific activity is *AFresh*, an AI service platform that supports grocers to optimize their perishable inventories with the use of AI. Therefore, their *activity focus specifically* targets logistics. On the other hand, AI platforms like *Amazon SageMaker*, which focuses on making ML model development feasible, target the *activity-unspecific* focus.

Platform use describes the AI service platform's integration from a temporal perspective. Organizations may apply AI service platforms to recurring processes (i.e., *continuous*) or solve a certain problem or a project-specific task (i.e., *on-demand*). This temporal perspective on service use can be traced back to characterizing the service provider-customer interaction in service marketing literature as either discrete or continuous to distinguish an episode of interaction from a long-lasting relationship (Liljander and Strandvik, 1995). For example, the AI service platform *KAI* continuously covers the interaction with customers. In contrast, *Domino Datalab* constitutes an example of on-demand use by providing a data science environment to develop, train, and deploy ML models.

4.1.2 AI platform's offering

The layer *AI platform's offering* consists of the dimensions *AI service model*, *complementary services*, *complementary resources*, *pricing model*, *code-based interaction*, and *graphical interface* that assess AI service platforms' offering and, therefore, its value proposition. This is in line with Gawer (2014): The *AI service model* (i.e., core) and *complementary services* and *resources* (i.e., periphery) describe the modular design of the AI service platform's offering. While the *pricing model* reflects the coordination mechanisms, *code-based interaction* and *graphical interface* depict the technological interfaces.

The dimension *AI service model* characterizes the nature of the AI service platform's offerings and therefore captures how an AI service platform creates value for the customer. Accordingly, the dimension *AI service model* distinguishes between different types and degrees of service integration. *Application deployment* and *application development and deployment services* directly enable a customer to build customized AI applications. Services targeting *application deployment* provide the infrastructure or assistance to deploy a ML model, which has either been built or trained on the AI service platform or stems from proprietary or public sources (e.g., local hard drive, repository, or cloud data storage). Businesses lacking the necessary infrastructure can use AI service platforms with a deployment environment to overcome long-term investments in infrastructure and benefit from maximum flexibility. Furthermore, they can receive support in the deployment processes if they lack knowledge. An example of an AI service platform providing a *deployment* environment is *Algorithmia*, which offers an automated service creating an API endpoint for a trained ML model callable from any application. Services for *application development and deployment* enhance *deployment services* by enabling the customer to build a model from scratch or customize existing models in terms of structure or parameters. Furthermore, such services allow for training proprietary or customized models to tune parameters. *Google Cloud AI Platform*, for example, provides a managed *Jupyter Notebook* service for customers to build their ML models using different ML frameworks. In contrast to *application deployment* as well as *application development and deployment services*, some platforms offer AI services providing instant model usage without actual access to the ML model (i.e., *ready-to-use service*). *Ready-to-use services* represent the most advanced offering of AI service platforms in terms of AI functionality. Customers can no longer access the ML model-level but can only decide to access or integrate the service and customize the service, not the ML model. Nonetheless, the service can improve by continuously learning from the customer's data. Examples include chatbots for specific industries, such as *KAI*, which offers a chatbot that is callable via an API by the customer's proprietary digital applications. Furthermore, AI service platforms may provide both *ready-to-use services* and customizable *application development and deployment services* that we consider as *hybrid* services. The characteristic *none* applies to the AI service platform providing none of the above services.

The dimension *complementary services* captures additional tasks of the AI workflow that can be crucial to applying AI successfully. Accurate data labeling, as an exemplary *complementary service*, is a critical success factor for supervised learning, which requires labeled output data for learning (Jordan and Mitchell, 2015; Hastie et al., 2009). Our sample includes data labeling platforms such as *Playment*, which incorporates a human crowd to label ground-truth data for training purposes without deploying ML models itself. The existence of the characteristic (i.e., *yes*) comprises AI service platforms offering items that support the use of AI in a complementary manner. The items are modular and moveable, even beyond the boundaries of the AI service platform. For example, *MLJAR* allows its customers to train pre-existing ML models and download them for local deployment.

The dimension *complementary resources* comprises supplementary elements required to develop or deploy AI services. Complementary resources include the provisioning of pre-trained ML models or readily-labeled and structured datasets. For instance, *AWS marketplace* provides pre-trained ML models to customers facilitating the development of AI services.

The dimension *pricing model* characterizes the pricing approach chosen by the AI service platform. As the use of an AI service platform versus the in-house development of AI represents an outsourcing decision, coping with costs and the desire for flexibility are central motivating factors behind the use of an AI service platform (Lacity et al., 2009). Therefore, the pricing approach of an AI service platform is of great interest to potential customers. As expected, this dimension appeared to be particularly relevant for the interviewed practitioners, especially those viewing AI service platforms from a customer perspective. Also, an attribute of cloud computing, a "pay-as-you-go" pricing mechanism (Hsu et al., 2014), is an equally suitable feature for AI service platforms. We captured the "pay-as-you-go" pricing mechanism in the characteristics *regularly based on variable rates* representing a high granularity of billing the AI service platform usage. As for pricing mechanisms of a rather traditional approach to IS/IT outsourcing (Hsu et al., 2014), we added the characteristics *regularly based on fixed rates* (i.e., a lower granularity of billing the AI platform usage) as well as *one-off payment* (i.e., a classic representation of a license purchase). In addition, we added the characteristics *freemium* and *free of charge*. *Freemium*-based business models provide basic services for free, while more advanced services are based on a fee.

The dimension *code-based service interaction* characterizes whether the customer can interact with the AI service by writing and running code in a development environment. For instance, *Algorithmia* provides customers with a client to work *code-based* in their preferred programming languages such as Python, Java, Go, and many others. Although the code-based service integration requires the customer to write code, it does not include integrating the platform's API.

The dimension *graphical interface* characterizes the modalities of interaction through graphical interfaces between the customer and the AI service platform. This dimension aims to indicate the critical skills required by the customer to use the AI service platform. The offering of the AI service platform can be leveraged by navigating on a graphical user interface (i.e., *click through*) or moving objects (i.e., *drag and drop*). Therefore, it captures whether the AI service platform enables the customer to work purely conceptual on a graphical user interface. For example, *AWS Marketplace* offers a graphical user interface for customers to *click through* their digital catalog and choose a matching listing. *Inbenta* provides customers with a *drag and drop* editor to create decision trees to customize their chatbot offering.

4.1.3 Third-party integration

Since the accessible innovative capabilities might stem from the platform provider itself or third-party agents (Gawer, 2014), we describe the platform's constitutive agents beyond the platform provider and customer in the *third-party integration* layer. The two dimensions of the layer *third-party integration* allow us to further assess AI service platforms' offerings regarding integrated complementors as well as the scope of integrated complementor offerings. Third-party integration is relevant for customers since it allows or facilitates access to complementor offerings by mediating technologically and/or socio-economically between the customer and complementor. Besides the practical relevance, this layer is also relevant for the scientific discourse regarding the definition of digital platforms.

The dimension *integrated complementor* distinguishes the complementors contributing to the AI service platform, if any. Observed third parties include *selected complementors* (i.e., restricted access to the AI service platform) or a *crowd* of complementors (i.e., open access to the AI service platform). An example of a *selected complementor* integration is *Civis Analytics*. This platform enables collaboration on a project by providing a GitHub integration, i.e., allowing GitHub as a complementor on its platform. An example of a *crowd* integration is the data-labeling platform *Playment*. They allow independent data-annotators to register on their platform to offer their customers a data-labeling service.

The *integrated complementor offering* further specifies the relationship between the customer, AI service platform, and complementor. The complementor can provide and receive *resources* (e.g., *Meya* offering backend resources such as a robust operating system) or provide a distinct *service* (e.g., the annotation service of *Playment* relying on a crowd of data-annotators). Also, the complementor of an AI service platform can provide both *resources and services* (e.g., *Inbenta* providing a chatbot that exchanges data resources with messenger tools).

4.2 Applying the taxonomy

Within this section, we describe our findings from applying the taxonomy to our sample of 31 AI service platforms. For this process, two of the authors have individually analyzed the publicly available information on the AI service platform providers' websites to classify them. By discussing the individual classifications, the two authors agreed on a uniform classification. Classifying the entire sample of AI service platforms allows us to hypothesize about underlying patterns (Nickerson et al., 2009).

Considering the dimension *industry focus*, we identified both characteristics (*industry-specific*: 12, *industry-unspecific*: 19). However, a closer look at the industry-specific AI service platforms reveals that only a few of them focus on a single industry. Most platforms focus on multiple specific industries. *Artivatic*, for example, provides a specific offer to multiple industries, namely insurance, finance, and healthcare businesses. In contrast, *BigML* also targets several industries (e.g., aerospace, entertainment, food, and transportation), but its offering is not industry-specific to that extent. The dimension *activity focus* indicates a one-sided distribution in favor of the activity-unspecific focus (27 out of 31). This accumulation is caused mainly by the platforms' focus on a set of activities. Thus, most AI service platforms in our sample have an indirect influence on the end-products of the customer. In our sample, the occurrences for the dimension *platform use* are evenly distributed. *Continuous* and *on-demand* services characteristics apply to respectively nine platforms in each case. Eleven AI service platforms offer both *continuous and on-demand* services. This joint occurrence is mainly due to AI service platforms offering *application development service* together with *deployment services*. Only two platforms provided neither continuous nor on-demand services (i.e., *none*).

Regarding the dimension *AI service model*, we particularly recognize AI service platforms offering *application development and deployment services* concurrently (13 out of 31). Three AI service platforms offer *application deployment services* only, while not a single AI service platform of our sample solely offers application development services. The remaining AI service platforms of our sample divide into nine platforms solely providing a ready-to-use service, three platforms offering a hybrid service model, and three platforms none of the defined service models. Especially well-established AI service platforms offer a wide variety of services. For example, *Amazon SageMaker* offers customers the primary AI service of providing an environment to develop and train ML models as well as enabling them to deploy their ML models through the platform. In addition, customers can use complementary services such as *Amazon SageMaker Ground Truth*, which allows them to access a crowd of data labelers to prepare their data for ML application. Furthermore, *Amazon SageMaker* offers pre-built *Jupyter Notebooks* as resources for common data preparation tasks or ML models, which can be used, adapted, combined, or amended. With roughly 77 percent of AI service platforms offering *complementary services* (24 out of 31), it becomes apparent that AI service platforms' offerings do not only target the primary AI service activities. Besides AI service platforms covering primary AI services, there are also AI service platforms that only offer complementary services (e.g., the data annotation platform *Figure Eight*) resources (e.g., the ML model and application marketplace *AWS marketplace*). *Complementary services* encompass, amongst others, the training of customer employees, a collaboration environment for AI service platform users, data labeling, engineering support, or the management of AI models in a portfolio or their version history. Complementary *resources* include pre-trained AI models that can be deployed or downloaded, customizable templates, or pre-built code for data preparation tasks. Overall, we observe that the modularity of AI service platforms greatly caters to the custom configuration of AI services and resources that a customer requires. In total, 10 out of 31 AI service platforms provide *complementary resources* to customers.

We had to exclude the dimension *pricing model* from the quantitative analysis as pricing information is often not publicly available. However, we regard the *pricing model* still as interesting, as it captures the superior cost predictability of outsourced AI functionality over developing in-house AI capability.

Further analyzing our sample of 31 AI service platforms, we found 18 platforms offering a *code-based service interaction* while 13 platforms do not offer code-based interfaces at all. Instead, these 13 platforms provide graphical user interfaces.

Considering the *graphical interface*, we observe all characteristics, however, with different quantities (*click through:* 20, *drag and drop*: 5, *click through and drag and drop*: 4, *none*: 2). Thirteen AI service platforms offer both a *code-based* as well as *click through* interaction to address customers with different levels of technical expertise. However, due to a varying need for technical know-how within one characteristic, it is necessary to evaluate the need for technical know-how on a continuous scale. Between the two extremes, the *drag and drop* interface allows for rather unrestricted development with little technical expertise.

Regarding the *third-party integration*, 17 out of 31 AI service platforms in our sample do not come with any third-party integration. The remaining AI service platforms either integrate *selected complementors* (7 out of 14), a *crowd* (5 out of 14), or both (2 out of 14). Integrating a *crowd* mainly follows the purpose of offering data annotation or a marketplace for ML models and applications. Regarding the integrated *complementor offering*, we found examples for each characteristic in our sample, although with different frequencies (*resource*: 4, *service*: 7, *resources and services*: 3).

5 Discussion

Against the background of examining and structuring the characteristics of AI platforms, we found that our resulting taxonomy and its application exhibit several further-reaching implications for research and practice. In the following, we provide a discussion of two major aspects: the prevailing motives of AI service platforms and the conceptualization of AI service platforms as digital platforms.

5.1 Motives of AI service platforms

First, we identified three prevailing motives of AI service platforms based on the conjoint occurrence of characteristics that were also noted in several expert interviews. We found that there are AI service platforms, which enable an organization to create its own AI models or applications with a high degree of freedom. This motive mainly includes AI service platforms offering rather generic AI development services, such as *Amazon SageMaker*. In this respect, the application of our taxonomy shows that AI service platforms often offer end-to-end services. Arguments in favor of offering an end-to-end service include, amongst others, the ease of use, operating costs, (technical) dependencies, and reducing complexity. However, even without taking the benefits for the customer into account, an end-to-end service enables the AI service platform provider to expand its scope of services. In contrast, a further reoccurring motive of AI service platforms is offering ready-to-use AI applications. Platforms classified hereunder provide integrated AI functionality whilst limiting the required development effort for customers. However, we observe that development platforms and ready-to-use AI services are on a continuous spectrum. An important implication of this finding is that organizations consequently require different levels of (AI) resources and capabilities for interacting with and leveraging the services of the respective AI service platforms. In addition, the customer's options for customizability resonate with the AI service platform's position on the spectrum. AI service platforms offering highly integrated services limit the degree of freedom of their customers as a result. We, therefore, characterize the motives at each end of this spectrum as the combination of (1) either high development effort and high degree of freedom or (2) low development effort and low degree of design and development freedom. We note that the classification of AI service platforms under this spectrum mainly relates to taxonomy dimensions regarding the primary AI services of the platform's offering as well as the customer context. It appears to be mainly independent of dimensions regarding third-party integration. Applying the taxonomy showed that the AI service platforms in the sample set are on a continuous scale between the motives presented. Choosing the right AI service platform, therefore, seems to be a matter of whether the customer searches for a specific, pre-developed AI service or wants to implement customizable AI applications independently. This directly influences the development effort that the customer must put into leveraging AI technology on top of what is already provided by the AI service platform. The extrema and a potential classification of AI service platforms, therefore, serve as an indicator for the required efforts the customer still needs to undertake as well as, in turn, the degree of design freedom the customer enjoys.

Besides targeting the primary AI services, we observe the third motive of AI service platforms focusing on secondary AI services, including complementary services (e.g., data labeling and ML model scoring) or access to resources (e.g., pre-trained ML models). These AI service platforms offer access to specific services or resources that are aiding the process of AI solution development.

Generalizing the taxonomy structure to a broader realm, our results highlight the modular design of today's AI service platforms. AI applications in practice serve many different purposes due to AI technology's potential to contribute to a wide range of promising use cases. Consequently, our results indicate that platform providers focus on providing rather modular service structures to facilitate the exploitation of provided services across a wide range of different use cases. Further, our taxonomy outlines the rich set of available AI services from data preprocessing to implementation and deployment. The provided services indicate the current state of innovation at the customer side: development and deployment of AI models are in full swing. However, services going beyond the deployment, such as model evaluation and management services, are only rudimentarily expressed.

5.2 AI service platforms and the digital platform definition

A second major aspect of this paper's discussion relates to the classification of AI service platforms as digital platforms per definition. A particularly salient aspect in this regard relates to the integration of third parties in AI service platforms. Most definitions of digital platforms view the platform's mediating aspect between multiple parties as an integral characteristic (e.g., Rolland et al., 2018; Reuver et al., 2018; Blaschke et al., 2019; Constantinides et al., 2018). However, in the definition as per Gawer (2014) that we rely upon, third-party integration is not necessary. Applying the taxonomy to our sample set shows that approximately 55 percent of all AI service platforms do not integrate any third parties at all. While this is in line with the broad and integrative platform definition introduced in Gawer (2014), AI service platforms are that diverse that they do not exclusively fit one of the specific platform perspectives (e.g., economic perspective). This finding suggests not making third-party integration a necessary condition. Nevertheless, we suppose that the integration of third parties in the context of AI service platforms can also occur through the integration of technological modules and services. Particularly some development platforms integrate modules developed by third parties, hence also providing a sort of mediation. Hence, the focus in this context is typically not on facilitating economic transactions as in a classical economic view on platforms. Nonetheless, there are also AI service platforms that integrate third parties by offering direct mediation of services, such as *Figure Eight*, which offers human resources for data annotation. However, the reason for our observation could also be a divergence between the public use of the term 'digital platforms' and definitions in the academic discourse. One interviewed expert even noted that his company does deliberately not call itself a platform anymore, as the term sometimes has a negative connotation with customers, who are skeptical that the service is simply calling itself a platform for marketing purposes rather than offering an actual valid service. In conclusion, our taxonomy could be a solid foundation to reduce the terminological ambiguities by revealing the true characteristics of digital platforms. Based on the development and application of our taxonomy and building upon the definition of Gawer (2014), we can characterize AI service platforms as follows: *AI service platforms provide organizations with access to AI technology to support them in creating or using AI applications through federating and coordinating constitutive agents, leveraging value by enabling economies of scope, and entailing modular technological architecture.*

AI technology in the context of this definition includes all levels of technological maturity on a scale from infrastructure optimized to deploy custom models via development environments to AI prediction services, which require little adjustment by the user. This AI service platform definition constitutes the first attempt to grasp the phenomenon of AI platforms by integrating both an economic and architectural perspective. We found that AI service platforms exhibit several intersecting characteristics that match with the technological platform definition by Gawer (2009). We, therefore, support this definition for digital platforms in general, as it is both broad and yet explicit enough to capture also the emerging phenomenon of AI service platforms as digital platforms. Our taxonomy generally provides literature with an overview of existing, relevant types of AI service platforms as well as their features, allowing scholars to develop definitions that are more in line with practical developments.

6 Conclusion

Aiming to examine and structure AI service platforms as an emerging phenomenon, our paper provides a comprehensive taxonomy systemizing the rapidly evolving landscape of AI service platforms in practice and considering their underlying characteristics. In doing so, we lay the foundation for a common understanding of AI service platforms in research. We established our taxonomy following the approach by Nickerson et al. (2013). The resulting taxonomy exhibits eleven dimensions, which we subsume under three layers. Our taxonomy integrates existing knowledge on digital platforms as well as a practitioners' perspective, ensuring both a theoretical foundation as well as practical relevance. The taxonomy adds to the descriptive knowledge on AI service platforms by increasing our understanding of AI service offerings available on the market. Furthermore, the taxonomy serves as a basis for interdisciplinary discussions complementing technical considerations. As a result, we provide an overview of the dimensions and characteristics of AI service platforms for practitioners, allowing them to make informed decisions about engaging with an AI service platform and the resulting implications for an organization. In doing so, the taxonomy can support practitioners in selecting an adequate AI service provider for the respective use case by defining the desired characteristics along the taxonomy's eleven dimensions and then choosing a suitable service platform. Moreover, the respective dimensions and characteristics also help practitioners in discriminating and comparing different AI service platform offerings and enable them to choose the right one according to their use case requirements. Apart from proposing the taxonomy, our theoretical contribution revolves around two further implications of our research. Through our taxonomy, we establish the foundation for higher-order theories. Thus, we found three main motives of AI service platforms, on a spectrum ranging from high development effort and high degree of design freedom to low development effort and low degree of design and development freedom. Additionally, we challenge existing definitions of digital platforms, in particular regarding the mediation aspect and integration of third parties. As a result, we propose a more generic definition for AI service platforms integrating existing perspectives and following Gawer (2009).

Considering our contribution to both academia and management practice, we acknowledge the limitations of our research and propose corresponding suggestions to address them in future research. First, we designed our taxonomy based on publicly available information on platform providers' websites, drawing from a representative yet limited sample set of 31 AI service platforms. Furthermore, we relied on the opinion of 14 practitioners for integrating the practical perspective. We, therefore, encourage future research to challenge and potentially expand our taxonomy by taking new developments in the rapidly evolving sample space of AI service platforms into account. This should include a practical application of our taxonomy to different AI service platforms in productive settings, incorporating customer experiences, for example. Second, we acknowledge to some extent giving up concrete applicability of our taxonomy as a decision template in practice for scientific precision and completeness. For example, with the meta-characteristic in mind, it became clear that taking a step towards a finer granularity of information would increase a manager's usefulness of our taxonomy. However, we realized that this would restrict the extent of generalizability of our research result and its relation to theoretical considerations of digital platforms. We, therefore, motivate research to review existing definitions of digital platforms in general, taking the public perception and positioning of providers of AI service platforms into account and providing more flexibility. Our AI service platform definition provides a first step towards this direction. Third, we encourage future research to derive and analyze archetypes of AI service platforms. Our discussion provides research with three qualitatively derived motives of respective platforms, therefore depending to some extent on the researchers' judgment. Archetypes, which describe generic occurrences of phenomena, may be developed using empirical cluster analysis (Everitt, 2011) that can be based on taxonomies describing the phenomenon (Fridgen et al., 2018; Haas et al., 2014). Fourth, adding on the derivation of archetypes, we recognize each analysis of the 31 AI service platforms as a static analysis not taking potential platform evolution into account. However, AI service platforms may evolve over time and change their characteristics leading to evolving classification. We, therefore, encourage future research to re-analyze the set of AI service platforms and investigate how platforms evolve over time. Potential change in the platform classification may allow the derivation of certain stages of platform evolution and increase the understanding of platform innovation. The taxonomy provides a useful tool to structure the analysis of platform evolution. Fifth, we emphasize the importance of elaborating on mechanisms and effects in the AI value network. This might include a discussion about the agents' roles or supremacy with respect to the democratization of AI. In summary, by creating and discussing the application of our taxonomy, we illustrate the relevance and potential of AI service platforms to serve as a gateway for organizations to employ AI technology. Sixth, we call on future research to integrate the organizational perspective on levering AI service platforms. While our taxonomy and the identified motives of AI platforms describe the AI service platforms themselves, a highly relevant aspect refers to the platform's customer side. We pose the questions, which customer resources and capabilities are necessary to successfully leverage AI (service platforms), and which types of AI service platforms best solve a customer's problems. Providing insights into the customers' integration of AI service platforms benefits both research as well as practice by providing a holistic view on the topic.

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