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Chapter 8

Plug and Play AI – How Companies Can Benefit from AI as a Service

Abstract: The vast possibilities of artificial intelligence (AI) have recently opened to a broad user base, for example, via ChatGPT. Entrepreneurs and innovators are increasingly developing AI-based products, and companies can solve problems with a growing range of available AI as a Service (AIaaS) products. However, there is only limited research available in the field of applied AI for business practices so far, maybe due to the novelty of the topic. We aim to build an initial step for theory in this field by putting AIaaS into the spotlight and forming the intersection of applied AI and its practical wildlife as AIaaS. We aim to contribute an empirically driven taxonomy of *Plug and Play AI* tools, a method common in information systems. Thus, we contribute to the theoretical foundation of AIaaS for further research and address practitioners with practical guidance in the broad AI application space.

Keywords: artificial intelligence, AI, NoCode, LowCode, ChatGPT, AI as a Service

8.1 Introduction

The recent development of artificial intelligence (AI) models and applications has faced many publicly known milestones during the last months. OpenAI's *Generative Pre-trained Transformer (GPT¹)* combined the existing language model with an easily

¹ See <http://chat.openai.com> (accessed 30 January 2023).

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Note: The views expressed herein are those of the authors and do not necessarily reflect the views of affiliated institutions.

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accessible and usable chat interface and might have defined a new level of user experience (UX) in terms of human–machine interaction with AI. This also applies to *DALL-E*,² a deep learning model also developed by OpenAI for creating digital images based on natural language descriptions, which offers a much better UX compared to existing alternatives like *Midjourney*³ (currently only available on Discord) or *Stable Diffusion*⁴ (currently only available for people with the hardware capability and knowledge to install and run machine learning models). Local startups like *neuroflash*⁵ built their product pipelines on top of such technologies and benefit from well-documented application programme interfaces (APIs) and transparent fees to form their own value proposition for their target audience. This illustrates how AI technologies face a major change: From technological, computer scientific, or engineering-driven systems to broadly accessible applications. Further, interfaces to use these AI technologies have changed radically. While access to and usage of AI models has been limited to programmers with certain experience in AI-oriented languages like Python for quite some time, nowadays, many applications are ubiquitous and require zero or very limited coding experience. The recent hype around apps like *Lensa*⁶ is illustrative for this shift, where social media has been flooded with AI-generated cartoon-like portraits. While these consumer-related applications gain much attention in public media, the academic community is facing an ongoing dialogue about the technological impact of language generation tools for scholars. Besides, the startup ecosystem is also facing major developments, as products can be designed with AI, built upon AI or sold with the help of AI-generated media content. Of course, this might also apply to existing business models. However, many AI models for enterprises and large companies were already existing before the above-described recent trend of AIaaS applications. Thus, the chapter focuses on the innovation and startup-related sector and the implementation of AI beyond classical programming. We are going to refer to this kind of AI under the umbrella term *Plug and Play AI*, which we are suggesting throughout this chapter as easily accessible AI (see also our extended working definition in Section 8.2). While AI model development and intensive programming (*ProCode*) is a field of interest for rather technical scientific areas, we want to bring *NoCode* and *LowCode* into the spotlight of our research contribution and form the intersection of economically relevant but technically less complex implementations of AI (Desmond et al., 2022). Therefore, we formulate the following research questions:

- (1) How can technologies, applications and code fragments under the umbrella of *Plug and Play AI* be clustered?
- (2) How can a taxonomy of *Plug and Play AI* look like?

² See <https://openai.com/dall-e-2/> (accessed 30 January 2023).

³ See <https://midjourney.com/> (accessed 30 January 2023).

⁴ See <https://huggingface.co/spaces/stabilityai/stable-diffusion> (accessed 30 January 2023).

⁵ See <https://neuroflash.com/> (accessed 30 January 2023).

⁶ See <https://prisma-ai.com/lensa> (accessed 30 January 2023).

The chapter is structured as follows: We first provide an overview of the relevant literature in Section 8.2. The research design is presented in Section 8.3, followed by the results of the data gathering and interpretation process in Section 8.4. We discuss our findings and derive implications for research and practitioners in Section 8.5 and conclude in Section 8.6.

8.2 Background

The rise of AIaaS represents a process towards the diffusion and ubiquity of applied AI for companies of all sectors and sizes (Sundberg & Holmström, 2022). For instance, modern banking and finance are intensively driven by outsourced IT services (Bhatia, 2022), including AIaaS. Another example is automation in marketing and sales, which includes creative, conceptual and semantic tasks (Gipp, 2021) and has become widely accessible through AIaaS for a broad range of industries. Even teaching and training, an area commonly known as an entirely human-focused one, has become a market for AIaaS providers, synthesising professional trainers, academic lecturers and professors (Pandey, Mishra & Tiwari, 2021; Synthesia, 2022). Nevertheless, the phenomenon of AIaaS and its relevance for both entrepreneurship and for grown companies and organisations have been underestimated. Potentially due to the interdisciplinary character of AIaaS: While computer science usually acts on a much deeper (technical) level, economics and management research would traditionally throw economic measures onto AI.

Taxonomy development for novel technologies is a fundamental contribution to the field of information systems, computer science and related disciplines. A major instructional study has been presented by Nickerson, Varshney and Muntermann (2013) and taken as a reference for taxonomic research projects since then. However, slight improvements and derivatives have occurred since then, including more practical recommendations for rigour and accurate taxonomy research designs (Kundisch et al., 2021). By far, not every new toolchain requires a taxonomy. Typically, infographics fill this gap for rather practical viewpoints nowadays, clustering applications in a visual form. Though, in the field of academia, taxonomies may help scholars to gain a basic understanding of a new learning field, and researchers can build their own research upon structure-providing contributions of others. For instance, Barn and Barn (2016) presented a cybercrime taxonomy, which they also thrived forward to an interrelated model of the discovered objects, basically generating an ontology as a result. Lempert and Pflaum (2019) created an Internet of Things (IoT) reference architecture based on their explorative IoT taxonomy development. For *Plug and Play AI*, we deem a taxonomy as beneficial notably because of its growing practical relevance and due to its novel character as a technology, further shaping future trends.

Another building block of our research idea is the way software is created (see Figure 8.1). In traditional computer science classes, we teach high- and low-level programming languages, programming paradigms and software architecture. In this chapter, we will refer to this paradigm as *ProCode*. However, recent years have brought broader acceptance of the so-called *citizen developer*, a rather visual and model-based approach of software design (Sahay et al., 2020). We believe that this trend is groundbreaking for the research purpose of the chapter: *Plug and Play AI* is easily attachable to existing data and infrastructure through such novel rapid development tools. To fasten up standard procedures, like CRUD database interactions (CRUD: create, read, update, delete) in combination with a simple frontend and sometimes individual code fragments, *LowCode* came up. Still managed under the responsibility of the IT department, developers with limited experience in certain technologies might be able to create business applications much faster than from scratch. Finally, *NoCode* forms a new kind of application development, significantly driven by three aspects: First, its UX-driven and visual appearance follow a state-of-the-art look and feel and makes it thus, second, usable for *citizen developers* with narrow technical knowledge. This is based on the gamified nature of *NoCode* tools, for instance, through direct visual feedback when a data connection between a *NoCode* app and a database has been established. Third, connectors of the so-called integration platform as a service (*iPaaS*) environment form a cloud-only ecosystem with easy-to-use APIs, making data linkage possible on scale.

For our work, we will combine *NoCode* and *LowCode* as *Plug and Play*, due to its easily applicable nature. Thus, our extended working definition for *Plug and Play AI*

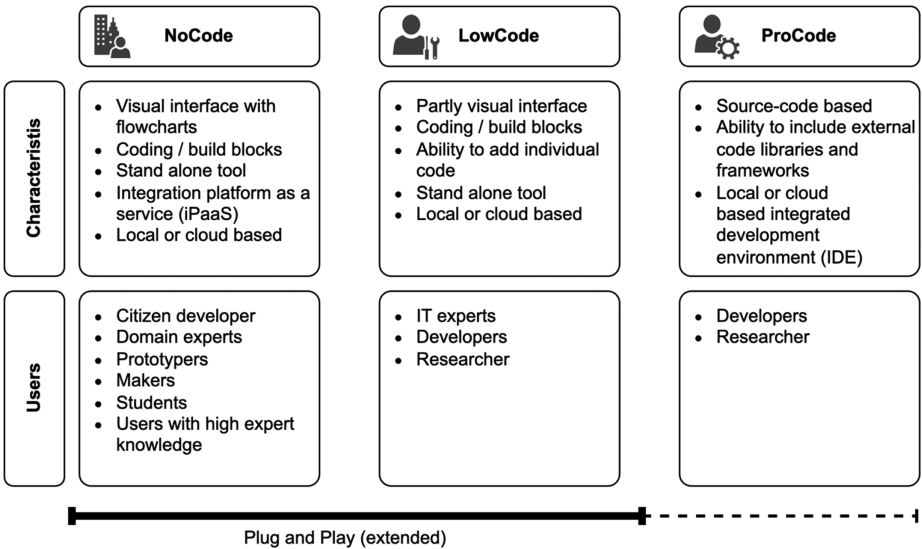


Figure 8.1: Characteristics and users for NoCode, LowCode and ProCode (adapted from Di Ruscio et al., 2022 and Desmond et al., 2022).

can be summarised as: An application (stand-alone or modularised), utilising AI methods (such as *Deep Learning*, *Neural Nets*, etc.), which is accessible and/or re-useable (in other software products) either without any (*NoCode*), with almost zero custom additional code (*LowCode*), in contrast to ProCode, where experienced coding skills are a prerequisite. In contrast to AIaaS, Plug and Play AI is not necessarily based on cloud infrastructure (Alla, 2020).

8.3 Research Design

We chose taxonomy design as an explorative paradigm for our research because the development and accessibility of such a novel technology (see Section 8.1) can hardly be accumulated into existing frameworks, definitions and research artefacts. Classification and taxonomy building for novel research fields is an important contribution for researchers and practitioners and the groundwork for later concepts to build upon, for example, semantic web technologies applying AI such as knowledge graphs (Van Rees, 2003). Taxonomy design is a well-elaborated and well-described method within the information system methodical landscape. The main concept, which has also been applied to this study, is based on an iterative data processing approach, including meta-characteristics and ending conditions, finally leading to a taxonomical hierarchy (Nickerson, Varshney & Muntermann, 2013).

As technological taxonomies are mainly driven by practice and industry, practical resources need to be taken as field data (Lempert & Pflaum, 2019). In order to find promising data sourcing of potential *No-* and *LowCode* AI firms, we first focused on the *German AI Association (KI Verband)* and accessed its membership companies ($n = 390$). Capterra ($n = 50$) and Producthunt ($n = 43$) were further, international, resources for curated lists of AI tools which we included, as well as seven other publicly accessible web resources (see Table 8.1). In total, different data gathering and crawling techniques delivered 553 potential companies or tools (referred to as suspects, including a title and a URL), whereof 504 went into our further data processing (the 49 remaining elements could have been eliminated immediately based on a first cross-check of title, headlines, etc.).

As a next step, we applied 15 filters to reduce our data to the defined scope (see Table 8.2). We eliminated AI tools that would not fit under our extended *Plug and Play AI* scope as defined in Section 8.2. As inclusion criteria, we defined that there should be a dedicated AI use case description available, to ensure that AI is the core of the respective tool in a transparent way. We also included only publicly available apps. In addition, we selected tools that are easy to use and access, in the sense that no specific IT knowledge should be required to use them. Further, tools with Business-to-Customer (B2C) focus were excluded, as this chapter focuses on AIaaS, thus only considering Business-to-Business (B2B) or Business-to-Business-to-Customer-relations (B2B2C). Finally,

Table 8.1: Discovered input sources. (compiled by authors.)

Source name	Suspects	Data gathering approach	Results
Geekflare	8	Manual access	10
KI-Bibliothek	6	Manual access	6
Capterra	50	AI-powered scraping with ScrapeStorm	49
KielAI	14	Manual access	8
KI Toolparty	29	Manual access (public content only, due to paywall)	27
VisualMakers	1	Manual access (dublette)	0
wemakefuture	12	Manual access	1
KI Verband	390	Python crawler	388
AI for All	43	Manual access	15
Total	553		504

we excluded tools that are not mentioned on a functioning website, as we deem this as a basic layer for validity of a tool. Lastly, we excluded duplicates. This resulted in a final list of 284 products which we then included into the further coding process.

Table 8.2: Applied filter criteria. (compiled by authors.)

Selection criteria (example)	Rule for exclusion (example)
Dedicated AI use case description (Exemplary description: “We use Random Forest Analysis to predict xyz . . .”)	Obviously non-AI, like regular tools, algorithms, etc. (Calendly was mentioned in some articles as AI tool, but it is obviously just a fancy booking application)
	Workflow automation tools (i.e., n8n is a tool for cloud automation and often mentioned when it comes to AI, but actually it is a visual API connectivity platform)
	Only claiming AI for Search Engine Optimisation or marketing purposes (i.e., “AI-powered” or “AI-embedded” without actual AI usage)
Public app	Tailormade AI/model (Exemplary description: “Together with an external software vendor, we built an AI model to . . .”)
Easy to use and access (limited IT knowledge and data management skills required)	AI frameworks for advanced AI experts (i.e., binaries, repositories, etc. which are only executable by experienced AI developers with extensive statistical knowledge)
B2B or B2B2C	B2C or fun products with no practical value (i.e., bodymaker is a personal sleep-tracking AI, or Lensa, an app that turns photos into art)
Website up and running	Tool not accessible through search engine / cannot be found

Next, we enriched the data set with two additional sources: First, we used OpenAI's API (text-davinci-003) to deliver us – where possible – a one-sentence description of each tool in our data set. The source code and the AI-generated descriptions are provided in our research data repository.⁷ While we had to try out different prompts, we learned that the quality and density of the answers varied significantly. Then, we used ChatGPT-3 (updated December 2022) for the same task and ran into technical restrictions quickly (limited input and output due to the non-commercial version used). However, some answers looked useful to us, and others (including our implemented termination commands) got ignored by ChatGPT. Thus, we decided to use the AI-generated description wherever possible, but only in triangulation with further data to apply cross-checks, as described as follows. To reduce the manual processing time, we implemented a web-crawling snippet to download the HTML title and meta-description from the URLs in our dataset. We found this step being helpful due to the high trust and informative value of the additional data, which is – presumably – generated by the companies themselves. We provide the complete data set on GitHub. While we used MaxQDA to build our final hierarchical coding structure, we made our research data accessible as a spreadsheet to maximise compatibility.

We chose a batch size of $n = 100$ per iteration for the coding process. According to Kundisch et al. (2022), the first coding iteration on our data followed an explorative nature, resulting in an initial coding set with the main coding classes:

- *Code-Level*: Describing the extent of understanding, writing or processing source code required to use the application.
- *AI-Level*: Categorising the technical characteristic of the data point, in terms of rather application-like or more abstract variants.
- *Users*: Coding class to describe different user types.
- *AI Use Case*: High-level category of the use case.

After the fourth iteration, we found that no further changes in our coding structure (including sub-classes) would be providing any additional value. This fits to the suggested ending criteria in literature (Nickerson, Varshney & Muntermann, 2013). We applied some further data validity checks within our research team to strengthen the objectivity of our results via independent checks and following discussions, but without further adaptations of our final results.

⁷ Our research data repository can be found via <https://github.com/nicolaikrueger/plugandplayai/>.

8.4 Results

First, we present the hierarchical order of classes and subclasses in Table 8.3. The full hierarchical tree can be accessed in our research data set, as we plotted only those subclasses with more than ten occurrences (see Table 8.3). We have found three types of AI levels, five types of users and accordingly roles in terms of their AI interaction and a wide range of Use Cases, which encompass sectors, such as *Marketing & Sales* or *Health, Pharma, Biotech*, as well as core features the respective products are providing on a cross-sectional basis, such as *Generative AI (Text)* or *Automation*. We also found ProCode tools in our dataset, which was unexpected due to our initial filtering. Those ProCode products can be classified as easily applicable but as part of the development and maintenance chain, for example, addressing users with cloud infrastructure management skills. As those products are somewhat in-between Plug and Play AI and ProCode, we decided to keep those tools as part of our results.

Table 8.3: Taxonomical classes, subclasses and frequency. (compiled by authors.)

Coding class	Subclass	Frequency*
Code-Level	NoCode	190
	LowCode	48
	ProCode	46
AI-Level	AI-Tool	156
	AI-Powered	69
	AI-Model	59
User	Domain Expert	136
	AI Scientist	66
	Anyone	51
	AI Operator	26
	Maker	5
AI Use Case	Rapid AI Model Development & Deployment	59
	Marketing & Sales	33
	Chatbot Platform	26
	Natural Language Understanding	21
	Generative AI (Text)	18
	Health, Pharma, Biotech	14
	Automation	13
	Manufacturing & Engineering	13
Business Analytics	11	

*Sub-classes with frequencies <10 have been excluded from this overview.

We further interpreted our data under the lens of user perception (see Table 8.4). Our taxonomy differentiates between five users according to different AI roles (*AI Scientist*, *AI Operator*) and business cases (*Anyone*, *Domain Expert*, *Maker*), respectively.

For a better understanding, in Table 8.4 we added one example per user which we have randomly chosen from our dataset.

Table 8.4: Users and AI roles in the field of Plug and Play AI. (compiled by authors.)

User	Description and goal	Example from the data
Domain Expert	Expert in a certain field, branch or occasion with the goal to apply AI in this field.	Mindpeak is a NoCode AI-Tool for Pathologists.
AI Scientist	Expert or scientist for AI as such with the goal to build, implement or maintain AI services.	Prenode is a decentralisation infrastructure model for AI scientists.
AI Operator	Prompt engineer, intensive AI user or admin for AI with the goal to run AI-driven tasks.	ChatGPT is an AI tool for generating text.
Maker	Product specialist with the goal to build a product upon (existing) AI tools.	QnA Maker is a chatbot platform which takes existing FAQ-HTML structure as input.
Anyone	Professional of any background with the goal to ease job tasks with the help of AI.	DeepL is an AI tool for translation and proofreading.

The AI levels defined in the taxonomy are *AI-Tools*, *AI-Powered* and *AI-Model*. While *AI-Tools* encompasses products which support users for a single task, *AI-Powered* refers to AI products which cover more complex tasks driven by AI technology. *AI-Model* represents the most advanced level. While we started our research under the perspective that we might find a clear match between AI roles and *Plug and Play* tools in terms of accessibility, applicability and so forth, the results are rather counterintuitive (see Table 8.5): Only the AI role *Maker* is not covered by model-based solutions in our dataset, all other combinations can be found. This could be explained by the business specificities required for product creation. For instance, anyone can train their own AI model using Google's *Teachable Machine*. Nevertheless, it is not suitable for building another product upon it (e.g., the *Maker* role), as it follows a more educational and explorative nature. Also, this phenomenon could be induced by the specific sources of our dataset. Another reason could be that AI products for *Makers* might have been excluded during our data selection process, as we excluded tools requiring advanced AI skills (see Section 8.3).

Table 8.5: Mapping AI roles and tools. (compiled by authors.)

	AI Operator	AI Scientist	Anyone	Domain Expert	Maker	Total
AI-Model	9	38	6	6	0	59
AI-Powered	2	16	34	13	4	69
AI-Tool	15	12	11	117	1	156
Total	26	66	51	136	5	284

Focusing on the contingency table (see Table 8.6) of code levels and use cases, it becomes evident that for our data in scope, most tools have been classified as *NoCode*. *LowCode* as well as the included subset of *ProCode* are quite underrepresented, with almost close to zero tools per use case, except for the rather technical use case *Rapid AI Model Development & Deployment*. In this specific use case, most tools are *LowCode* and even a substantial number of *ProCode* tools could be identified. For most use cases in our data set, apparently no coding skills are required at all.

Table 8.6: Mapping code level and use cases*. (compiled by authors.)

	NoCode	LowCode	ProCode	Total
Automation	10	2	1	13
Business Analytics	8	2	1	11
Chatbot Platform	25	1	0	26
Generative AI (Text)	16	1	1	18
Health, Pharma, Biotech	8	2	4	14
Manufacturing & Engineering	9	1	3	13
Marketing & Sales	30	2	1	33
Rapid AI Model Development & Deployment	15	27	17	59

*Use cases with a total occurrence of <10 have been excluded from this overview for relevance reasons.

8.5 Discussion and Outlook

Interdisciplinary research on AIaaS is still rare. The recent debate about ChatGPT and other generative AI tools has intensified the discussion, relevance and knowledge seeking in this research area. First, this chapter contributes to this field by offering a more practical term and definition for AIaaS: *Plug and Play AI*. Under this umbrella term, for which we also provide some background and differentiation based on the literature, we include *NoCode* and *LowCode* solutions with AI-character and also *ProCode*, though the latter to a limited extent. Thus, the field of *NoCode* and *LowCode* approaches can also benefit from the findings of this chapter. We believe the provided taxonomy in Table 8.3 is beneficial for researchers as it represents a structured first theoretical contribution in the rather new field of AIaaS. Furthermore, we want to encourage researchers to continue an interdisciplinary discussion and research in this field and therefore, we make our data set public. The implications for practitioners are as follows: IT decision-makers can benefit from this chapter by the provided landscape of tools we collected for generating the taxonomy. While our data set is limited by the fact, that it does not cover all existing tools in this rapidly developing market, it can nevertheless help to find valid selection criteria for decision-makers.

We believe that we can contribute to the benefit of other scholars, academics and practitioners by providing data and code.

8.6 Conclusion and Outlook

The aim of this chapter is to reframe the academic discourse of AI under the lens of recent AI applications, like ChatGPT, which represents a new, ubiquitous and easily applicable category of AI tools or elements. We approached this phenomenon with an explorative view based on existing tools in the field, conducting an empirical analysis. We provide a taxonomy to build a first theoretical understanding of AIaaS, which can help practitioners, for example, during technology and startup scouting, but also support scholars for a better understanding of the interdisciplinary nature of such AI applications. In future research, we aim to thrive our data forward towards an ontology to explore underlying AI models, code libraries and tools. This might be achieved on the basis of interpreting code dependencies on GitHub, at least for those applications listed in this chapter, which are open source.

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