When Standard Is Not Enough: a Conceptualization of AI Systems' Customization and its Antecedents

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Completed Research Paper

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Abstract

The centrality of information systems (IS) customization to match companies' needs with software systems available in the market has been researched extensively. The distinctive characteristics of Artificial Intelligence (AI) systems compared to other types of IS suggest that customization needs a new conceptualization in this context. We draw on evidence from expert interviews to conceptualize customization of AI systems as composed of four layers: data, models, algorithms, infrastructures. We identify a continuum of levels of customization, from no to complete customization. Since companies customize AI systems in response to business needs, we develop a theoretical model with six antecedents of AI systems' customization choices. In so doing, we contribute to both AI management research, by introducing the IS customization perspective in the field, and IS customization literature, by introducing AI systems as a novel class of systems and enlarging the understanding of customization for a specific class of software systems.

Keywords: Artificial Intelligence, AI customization, IS customization, AI implementation

Introduction

Artificial Intelligence (AI) systems have the *"ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals"* (Kaplan and Haenlein 2019, p.17). Recent studies indicate that companies adopting AI systems have increased in the last years and that a vast majority of large firms plans to further increase their AI investments (Davenport and Bean 2022). Consequently, more and more organizations are considering AI as a pivotal means to support and enable value creation.

As with other information systems (IS), companies face the question of whether to "buy" a standardized AI system from the market or "make" their own one (Rands 1993). While the "buy" approach fully relies on the external market, the "make" option entails taking care of development and training activities internally, while facilitating part of the process through pre-built components such as models, algorithms, or data sets. Either way, firms confront a vast and fast-changing landscape of commercial and open-source AI offerings that support the creation of AI systems. They can run on-premises or in the cloud and include software packages featuring different machine and deep learning algorithms (Overgoor et al. 2019), plug-and-play AI solutions (Ridhawi et al. 2021), cloud-based "drag-and-drop" AI tools to build new models (Rai et al.

2019) and ready-to-use APIs for specific applications (Davenport 2018)[1]. Although similar at a first glance, these AI products are highly diverse (Yao et al. 2017). The spectrum reaches from black-box standard software for narrowly defined use cases that does not even allow to examine the model used for predictions (e.g., standard computer vision APIs), to configurable offerings that retain ample room for customization allowing to develop, adapt, and fine-tune models (e.g., frameworks to develop virtual assistants) as well as open-source offerings to build fully customized AI systems from scratch (e.g., frameworks) (Yao et al. 2017). Consequently, firms must not only decide whether and how AI can enable and support their value creation, but they also need to find the best match between their idiosyncratic requirements and the right level of customization of their AI system, sourcing from this variegated market. Hence, the question of determining an appropriate level of customization of an AI system is a complex challenge that is not only driven by the dynamics of the market but also by the ambiguity of underlying business requirements, as most organizations are making their first steps towards AI, so that goals and use cases are not yet fully stabilized.

Recently, research in the field of IS and general management has focused on several emergent issues that relate to "managing AI" (Berente et al. 2019). Research on managing AI has focused on multiple topics, including AI innovation capabilities (Lou and Wu 2021), AI strategic orientation (Li et al. 2021), and human-AI augmentation (Fügener et al. 2021; Teodorescu et al. 2021). This research underlined that companies still face significant uncertainty on how to manage AI and that we lack understanding of how established knowledge on managing IS translates to AI systems (Berente et al. 2019). Despite the growing number of companies exploring AI as a crucial mean for value creation, little attention has been devoted to exploring how firms can create AI systems in line with their own company's requirements, given the vast and confusing landscape of AI products that support different levels of customization. These questions include how companies source AI systems, the acquisition of AI products from the market and their customization to meet companies' business needs. Similar key questions have been widely explored in the traditional IS domain but remain under-researched in the field of managing AI systems.

On the flipside, the IS literature extensively explored similar issues. Within the discourse of sourcing IS through make or buy approaches, several authors covered the acquisition of software from the market (e.g., Sawyer 2000) and the need for different levels of their customization as a crucial means to match market products with the idiosyncratic characteristics of the adopting organization (Holland and Light 1999; Sawyer 2000). Such match has been recognized as a key factor for successful software implementations (Xu and Brinkkemper 2007; Stefanou 2001). However, recent research has clearly shown that AI systems are different from traditional IS from several points of view, among which the provision of human or super-human capabilities (Pentland et al. 2020) through self-learning algorithms that learn from data (Teodorescu et al. 2021). These differences impact the key features of AI systems compared to traditional IS and could result into completely different levels where customization can happen, as well as different considerations and factors that drive sourcing and customization decisions of companies. This suggests that we cannot simply translate current IS knowledge on software acquisition and customization to the field of AI systems, but rather that the concept of customization needs to be reexamined in the context of AI systems, as it might constitute a different concept and be driven by different factors.

To address this research gap, this paper explores the intersection between research on managing AI systems and IS customization. Therefore, this study answers the following research questions:

RQ1: *How can we conceptualize the customization of AI systems?*

RQ2: *Which antecedents explain the need for high levels of customization of AI systems?*

To answer these questions, we conducted 24 qualitative interviews with experts from organizations implementing AI systems. Following an explorative and inductive approach, we developed a conceptualization of customizing AI systems. Our data suggests that AI systems can be customized in four different layers: data, model, algorithm, and infrastructure. We show that these layers can be customized independently from each other and can explain different AI systems' customization levels in a continuum that ranges from no customization, i.e., sourcing a standard AI product from the market to complete customization, i.e., developing an original and completely company-specific system. Going one step further, we develop a theoretical model explaining levels of AI systems' customization in organizations. In greater

[1] For simplicity, in the remainder of this paper we refer to these commercial and open-source offerings available in the AI market with the comprehensive term "AI products".

detail, we find that the choice of levels of customization of AI systems is guided by six antecedents such as the idiosyncrasy of the business problem, the availability of distinctive training data or the need for AI experimentation. This paper brings three main contributions. First, we contribute to the AI management literature by the introduction of the IS customization perspective to this research field and we offer a conceptualization of AI systems' customization that is grounded in the unique properties of AI. Also, we investigate antecedents of organizational AI systems' customization choices, i.e., high or low levels of customization. Second, we contribute to the IS customization literature through the introduction of AI systems as a novel class of software systems, and a better understanding of customization for specific software systems. For practice, our paper contributes by helping companies in sourcing appropriate AI systems and components from the market and by providing decision-making support to determine the needed level of customization.

The remainder of this paper proceeds as follows. In section 2, we elaborate and present the conceptual background on AI systems' management and the AI market landscape, as well as IS customization. In section 3, we outline our methodology, which is followed by the presentation of our results in section 4. Finally, theoretical and practical implications are discussed in section 5, and areas for future research are presented in conjecture with this work's limitations and conclusions in section 6.

Conceptual Background

This section provides relevant background information on the management of AI systems and IS customization. First, we discuss current research on managing AI systems. Second, we discuss IS customization in previous literature and how the characteristics of AI systems might impact this concept.

Managing AI Systems

AI systems can perform actions typically associated with humans, such as perceiving, reasoning, learning, and interacting (Rai et al. 2019). When deciding how to source AI systems, companies can leverage a vast and diversified AI market that offers a wide spectrum of options.

These options have been touched by several contributions which presented different examples, classifications and typologies. Some authors presented a classification of three categories of AI products, distinguishing among environments where to write code from scratch, pre-built packages in programming languages, and plug-and-play software that provides user-friendly tools (Overgoor et al. 2019). Others touched upon the concept of "packaged analytics" and "off-the-shelf AI" as ways to implement AI systems reducing the need for technical skills (Carvalho et al. 2019). Research also explored a distinction between the design of in-house AI and the use of AI as a Service (AIaaS) (Pandl et al. 2021). Consistently, Rai et al. (2019) presented the market of AI cloud-based tools, including open-source frameworks, drag-and drop-tools to build models and APIs for specific purposes. This market covers the whole spectrum of the trade-off between control and complexity, leaving companies in front of a set of options that range from standardized systems where no parameter can be set, to fully configurable ones where several parameters need to be selected based on the firm's needs. Yao et al. (2017) highlighted how more control over the development and implementation process can allow expert users to build higher quality AI models, as choices on data management, algorithms, and parameters' tuning can have impacts on the performance of AI systems. However, successfully managing this higher control also requires coping with higher complexity. On the other hand, when AI products limit complexity, it can remain unclear how and to what extent products can successfully manage development and implementation activities such as data preparation, model development, and parameters tuning which go into building a functioning AI system. Despite such variegated landscape, research still needs to explore how companies leverage and customize this spectrum of options to implement AI systems, balancing the complexities of customization with the need to meet their requirements. Consistently, Berente et al. (2021) highlighted that AI comes with complex challenges, and significant uncertainty remains on how to manage AI systems.

A relevant part of the recent IS debate on AI is focusing on the emergent issue of "managing AI" (Berente et al. 2021). The AI management literature starts from the understanding that AI systems add further levels of novelty and complexity to the design, implementation, and management of IS. Therefore, it aims to assess the extent to which we need to adapt and reinvent IS knowledge in the context of AI systems. Research topics in the scope of AI management are broad, and include, but are not limited to, the management and governance of AI systems, organizational implications of AI, and design issues with AI (Berente et al. 2021). So far, studies have dealt with the creation of AI innovation capabilities (Lou and Wu 2021), AI performance assesment (Lebovitz et al. 2021), AI strategic orientation (Li et al. 2021). Great attention has been devoted to the topic of human-AI interaction and augmentation (e.g., Teodorescu et al. 2021; van den Broek et al. 2021). Other recent contributions in the adjacent field of "AI in organizations" (Benbya et al. 2021) have focused on the safe deployment of "inscrutable AI" (Asatiani et al. 2021), and the impact of AI on employees' professional roles in organizations (Strich et al. 2021). However, little attention was devoted to exploring how firms seek a match between their business needs and AI systems, while navigating the complex landscape of AI products. Nonetheless, the centrality of this question for successful IS implementations has been widely recognized by both companies and academia for other types of IS, with extensive research that explored the sourcing of traditional IS, and their customization to match market offerings with companies' requirements (Cox et al. 2012). Research also highlighted how the successful match between software products and the firms' idiosyncratic business characteristics is a key success factor for implementations (Xu and Brinkkemper 2007; Stefanou 2001). Despite this previous IS research, we still miss an understanding of how companies make similar decisions in the emergent field of AI systems.

IS Customization and Implications for AI Systems

The problem of IS sourcing has been widely explored in IS literature. It mainly deals with the issue of how to carry out the IS-related activities necessary for a company to deliver its business proposition through a combination of internal and external IS resources (Martensson 2001). Within the IS sourcing literature, the make-or-buy literature is the most focused on specific IS acquisition decisions. In proposing his framework for make-or-buy decisions, Rands (1993) highlighted that one of the options within the "buy" is the use of software packages offered by providers. Over time, extensive literature has explored the problem of implementing IS through software systems available in the market. Literature suggests that finding the best fit between functionalities of these standardized software products and business needs is fundamental, as it helps successful implementation and usage (Xu and Brinkkemper 2007; Stefanou 2001). However, this fit can be problematic, as these solutions are built with generic users in mind and often do not translate easily between companies and industries (Pollock and Cornford 2004). Therefore, not only they need integration with existing systems, but they also typically require some customization to the idiosyncratic business characteristics of the adopting organization (Murphy and Simon 2002).

Literature has provided several different definitions of software customization (Cox et al. 2012). In general, customization can be seen as a response to a lack of fit between an organization's business characteristics and those envisioned by the solution designers, to bring it more in line with nonstandard business needs (Gattiker and Goodhue 2005). Three main perspectives have been presented about customization. First, some authors conceptualize it as a modification to a system's source code not originally supported by the solution (Dittrich et al. 2009), pursued through modification, addition, or change to specific functionalities (e.g., Parthasarathy and Daneva 2016; Light 2001). Second, other authors associate customization to the adjacent concept of software configuration. Configuration is defined as the process of setting all the usage options available in a software to reflect organizational features (Davenport 1998). In this case, customization is framed only in terms of the chosen configurations of parameters offered by the provider without changing the solutions codebase directly. Third, other authors bridge the two previous perspectives. Luo and Strong (2004), Haines (2009), and Brehm et al. (2001) argue that customization can entail a spectrum of options. While some only include the configuration of parameters, others entail deeper modifications not supported by vendors. More recently, customization literature has considered new categories of cloud-based software products, such as Software as a Service (SaaS). Due to multi-tenancy, here customization takes the shape of configuration of a vast set of parameters and options offered by SaaS products, which can happen at different architectural layers (Ali et al. 2019; Seethamraju 2015).

Although the field of IS customization has a long research tradition, a connection between the customization of IS and the field of AI has not been drawn yet. In fact, there is currently little conceptual understanding of customization and its levels in the domain on AI systems. However, recent contributions have underlined that AI systems are different from traditional IS along four main dimensions. First, AI systems are equipped with distinctive cognitive capabilities, that go beyond pure automation and constraints of human intelligence (e.g., Berente et al. 2021; Ransbotham et al. 2020). Second, AI systems depend on data for self-learning, meaning that their predictions are based on training data observed from practice and not explicitly based on human-defined rules (e.g., Fügener et al. 2021; Teodorescu et al. 2021).

Third, AI systems introduce new forms of human-machine interaction, empowering new and different types of human-machine augmentation (e.g., Rai et al. 2019; Benbya et al. 2020). Fourth, AI can impact agency, introducing questions over who is responsible for the implications of actions automated by AI systems or based on AI insights (e.g., Berente et al. 2021; Benbya et al. 2021).

These differences between AI systems and traditional IS also impact the traditional conceptualization of IS customization. In fact, there is little evidence of whether the knowledge of IS customization also applies to AI systems. Literature on IS customization highlighted several connotations of customization. Customization could entail a modification of a system's source code (Dittrich et al. 2009), the configuration of parameters to reflect organizational features (Davenport 1998) or a combination of the two on a spectrum of intermediate options (e.g., Brehm et al. 2001). Literature also pointed to customization as an activity that can happen at different architectural layers of a system (Ali et al. 2019). The differences between AI systems and IS could have impacts on all these characteristics of customization as they have been conceptualized so far and thus question whether our current understanding of IS customization can be applied to AI systems as well. For instance, the provision of new cognitive capabilities through self-learning implies a new and different role of data compared to traditional IS, as it is now used to train AI algorithms. The role of training data and the presence of AI algorithms could result into different layers where customization could happen and change what constitutes the system's source code to modify or the available parameters to configure during customization activities. This could also have repercussions on the spectrum of customization options available. Moreover, the new forms of human-machine interactions and the consequent impacts on agency and accountability could imply a higher need for company-specific adaptations, reducing the push to pursue standardization and best-practice processes typical of several packaged systems. This could lead to different considerations in seeking a match between AI systems and the idiosyncratic needs of single organizations. Therefore, these unique characteristics of AI systems suggest that AI systems' customization could be different than traditional IS customization as we understand it today.

Methodology

Data Collection

The empirical data was collected through 24 semi-structured expert interviews, representing 27 organizations operating in Europe. All participants are subject matter experts that have a proven experience in the acquisition and implementation of AI systems in a variety of industries. We ensured that different company sizes were represented and that they were engaged into several different types of AI initiatives. Thereby, we aimed to comprehensively cover a variety of perspectives through a maximum variation purposeful sampling strategy (Patton 1990). Gioia et al. (2013) suggest that organizational phenomena are socially constructed by knowledgeable agents who can explain their thoughts, intentions, and actions. Since the study involves both technical and decision-making topics, we selected participants that have a comprehensive overview of AI systems and their acquisition. We iterated multiple times between data collection and analysis. Our data collection started with a first group of subject matter experts to form an initial understanding of how companies acquire AI systems and customize them. After a first round of data analysis following the approach described in the section below, we enlarged our sample. This allowed us to progressively refine our understanding. We stopped interviewing when the evidence from data analysis had stabilized and we perceived that we had reached enough evidence to come to purposeful synthesis, following the data saturation and data sufficiency criteria for qualitative data collection (Shaheen et al. 2019).

Before the interviews took place, we informed the participants about the study details and gave assurance about the ethical principles of anonymity and confidentiality. This gave respondents some idea of what to expect from the interview, increased the likelihood of honesty and was also a fundamental aspect of the informed consent process (Gill et al. 2008). The interviews focused on questions regarding the acquisition of AI systems from the market and their implementation, the extent of configuration of such systems, the main factors driving the choice of a system over another and the reasons behind the need for deeper levels of customization. All the informants were encouraged to discuss these topics with their own terms and concepts, avoiding the excessive use of existing terminology to discover new concepts (Gioia et al. 2013).

All the interviews were conducted via video or phone calls. The interviews were audio and video recorded after consent was granted and transcribed for further analysis. On average, the interviews last 45-60 minutes and were conducted individually to avoid distortion among participants. We also used publicly available materials from companies' websites and reports to gather further contextual information and interpret the empirical data when necessary. Table 1 provides an overview of the data collection phase.

Informant	Industry	Job Title	Duration
1	Telecommunications	AI Project Manager	60'
2	Chemistry	Chief Digital Officer	55'
3	Chemistry	Digital Project Manager	55'
4	Energy and Utilities	AI Advisor	50'
5	Pharmaceutical	Lead Optimization Laboratory	55'
6	Energy and Utilities	Data Platform Practice Manager	60'
7	Telecommunications	Chief Information Officer	50'
8	Information Technology	Head of NLP Center	55'
9	Information Technology	Head of Data & Analytics	55'
10	Metals and Mining	AI Advisor for Manufacturing	50'
11	Financial Services	Business Intelligence Consultant	60'
12	Financial Services	Founder and CEO	60'
13	Telecommunications	Virtual Assistance Manager	55'
14	Telecommunications	Digital Project Manager	55'
15	Automotive	Director, EMEA – Central Europe	50'
16	Energy and Utilities	Manager, AI & Automation Services	45'
17	Energy and Utilities	Head of Hydrogen Business Units	45'
18	Telecommunications	Head of Predictive Maintenance	60'
19	Media and Broadcasting	Digital Strategy Consultant	60'
20	Media and Broadcasting	Digital Strategy Manager	55'
21	Information Technology	EMEA AI Practice Lead	50'
22	Information Technology	Head of Advanced Analytics Center	50'
23	Food and Beverage	AI Business Development Manager	55'
24	Information Technology	Partner, AI Practice Lead	60'

Table 1. Details of the Interviews

Data Analysis

To systematically extract information on the acquisition of AI systems, their customization and the driving factors behind such choices, we transcribed and coded all interviews. Codes are labels that assign symbolic meaning to the descriptive or inferential information gathered through a study (Miles et al. 2018). We used them to retrieve and categorize information in interviews transcripts to cluster elements that relate to a particular construct or theme (Miles et al. 2018). Codes were used to conceptualize customization in the context of AI systems, understand the ways in which customization is achieved and identify the driving factors that influence the need for high levels of customization. In doing this, we followed the data analysis approach proposed by Gioia et al. (2013) and Miles et al. (2018). This methodology has been recently adopted in other explorative studies in the field of AI (e.g., Schaefer et al. 2021; Seppälä et al. 2021). We chose this methodology to guide the analysis process for two reasons. First, it provides a systematic guide on how to code the data. Second, it focuses on creating a data structure that visualizes the analysis process (Gioia et al. 2013).

We applied a multi-stage coding scheme, which allowed to identify a "data structure" that visualizes how 1st order codes, 2nd order categories, and aggregate dimensions relate to each other. In the first stage, we started from transcripts and identified 1st order codes, which represent themes directly emerged from informants during the interviews. They either derive from meaningful terms used during the interviews or reflect their underlying meanings (Gioia et al. 2013). Similarly, we analyzed in the same way public documents and texts suggested by informants (e.g., websites, public cases) to validate statements and find additional aspects relevant to the study. We used our research questions to guide our first round of coding. In the second stage, similarities and differences were identified in the initial codes to reduce them to a more manageable number and 1st order codes were progressively refined according to our evolving understanding. We then proceeded to organize them into 2nd order categories based on their similarities in contents and logical connections. The second stage of the data analysis resulted in 43 1st order codes and 17

2nd order categories. In the third phase, our 2nd order categories were reexamined, looking for underlying connections at a higher level of abstraction. The output of this phase led to the identification of 7 aggregate dimensions. In the fourth stage, we compared our results with the relevant literature highlighted in the conceptual background to see how our data structure relates to it and whether new concepts had emerged.

Throughout the data analysis, we took several measures to ensure a rigorous research process and trustworthy interpretations of evidence (Lincoln and Guba 1985). First, we followed the Gioia method to make the process transparent. In fact, this method was designed to bring rigor to qualitative research (Gioia et al. 2013). Second, two researchers were involved in the coding process. Following Saldaña (2021), that highlights the importance of coding as a collaborative effort to develop a more objective perspective on codes and their interpretations, we went through multiple iterations to reach a consensus on the appropriate usage of the codes (Saldaña 2021; Harry, Sturges, and Klingner 2005). Third, we discussed preliminary results with informants throughout the research and asked opinions and feedback to other colleagues. We changed and updated the concepts whenever suitable, thereby testing our codes for clarity and reliability (Harry et al. 2005). We repeated these iterations until we reached consensus on the dimension of customization for AI systems and its components, as well as the antecedents of high levels of AI system customization. Fourth, the results come with informants' quotes and own words to make their experiences and opinions as explicit as possible. The data structure for AI systems customization and its antecedents are presented in Figures 1 and 2 in the Results section.

Results

Drawing on the findings from our analysis, we first offer a conceptualization of customization for AI systems based on four dimensions connected to the peculiarities of these systems compared to other IS and identify a continuum of levels of customization for AI systems. Second, we provide evidence of six antecedents, which explain different levels of desired customization for such systems.

Conceptualizing Customization for AI Systems

Customization Layers for AI Systems

Our data analysis allowed to conceptualize AI systems' customization as the set of activities that companies pursue to create AI systems in line with their business needs and constraints. The creation of such systems can happen through a variety of means. Consequently, also the pursue of a match between business requirements and an AI system can take different shapes. Some respondents referred to AI systems' customization as the implementation of AI systems by combining several components that streamline part of AI development to create *ad hoc* applications. For instance, a representative from a large telco company recalled that they "*built AI combining components from cloud providers, open-source frameworks, and internally developed tools in a platform. With that, data scientists build and deploy new AI consistently*". Other informants instead source AI systems through standardized products readily available in the market and refer to customization as the configuration of parameters offered by these products. Depending on the company's needs and the configuration features supported, customization can imply different activities. For instance, an AI Advisor at a major energy company highlighted that the company "*leveraged an AI product from a cloud provider but trained a new model from scratch through its own data and one of the many algorithms supported by the solution*". Differently, another large firm in the same industry decided to automate part of its back-office activities through an AI system that relied on a cloud product with an embedded pre-trained NLP model that only needed a small refinement through additional training data.

We found that companies can customize their AI systems differently, acting on different elements of the system. Through the Gioia methodology (2013) we identified a data structure for the customization of AI systems. Figure 1 provides the results of such data structure. In the following sections, we refer to the 2nd order categories shown in the figure as "layers" of customization for AI systems. Specifically, the concept of AI systems' customization is composed of four layers: data, models, algorithms, and infrastructures. AI systems can be customized independently at any of these layers.

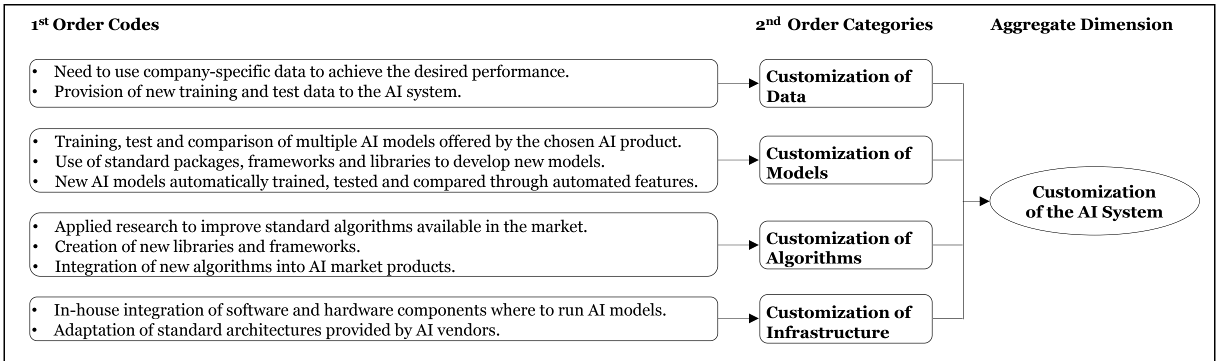

Figure 1. Coding scheme of Customization for AI Systems

Customization of data refers to the provision of new company's training data to an already functioning AI model. AI systems rely on self-learning algorithms that learn from training data to generate new predictions (Fügener et al. 2021). Therefore, the provision of new training data can help to contextualize them to the domain of the adopting company. As reported by the Founder and CEO of a tech company operating in Financial Services, "*several AI products in the market are equipped with standard models pre-trained on some data. They already work in generic cases, but if companies want something more specific, they need to provide their own case-specific data for further training*". The use of case-specific data adapts a generic AI model to the requirements of the company. For instance, a Digital Strategy Consultant at a global leader in media and broadcasting highlighted how they were customizing a speech-to-text and an image recognition product from an AI provider with data specific to their news channel to create an AI system able to automatically detect the meaning of a text and associate it to appropriate images.

Customization of models refers to the creation of AI models through the training, testing and comparison of available AI algorithms through problem-specific data. When pursuing model customization, companies only use state-of-the-art algorithms available in the market that are recognized as relevant options for the problem and they experiment with them to develop the best AI model. This means that although new AI models are created using one or more algorithms, there is no specific work that goes into customizing the characteristics that define such algorithms which were previously created by research centers or represent widely well-known options. As recalled by a manager responsible for the data platform of an energy company, talking about a predictive maintenance project for offshore facilities, "*we sourced the necessary data and used it as input to the AI platform by Microsoft Azure. We used two well-known algorithms supported by the platform which are recognized best practices for these use cases*".

Customization of algorithms refers to the development or tuning of the inner structure of AI algorithms, going beyond consolidated approaches. Customizing algorithms implies the modification of their inner functioning or their improvement compared to standard options to seek a better match between business requirements and the AI system. As recalled by two AI leaders with strong technical backgrounds at an Italian IT company, when the usual best-practice AI algorithms do not provide sufficient performance, companies can develop new approaches through incremental improvements that "*open the standard algorithms commonly available in Python libraries to make them better for their objectives*".

Customization of infrastructures refers to creating an *ad hoc* enabling infrastructure for the AI system. We found that when companies act on the infrastructure layer of their AI systems, they prefer not to rely on the reference infrastructures offered by market products but rather adapt them or assemble the enabling components by building them in-house or by sourcing them from the open-source world. Informants referred to infrastructure customization as "*build a fully customized tech stack for AI*", "*create in-house a comprehensive architecture with all the hardware and software components necessary to run AI*", or "*assemble a vendor-independent backbone with all the connectors to connect with legacy systems and to orchestrate AI products from multiple providers*".

Levels of Customization for AI Systems

We found that companies can customize AI systems by acting on the presented customization layers in different ways. A continuum of levels of customization for AI systems emerged from the data analysis. This ranges from "no AI systems' customization" to "complete AI systems' customization". While in the former companies do not act substantially on any of the customization layers presented, in the latter extensive customization happens at every level. Between these two extreme cases, companies can make a large variety of different customization decisions. Therefore, companies can give rise to several different intermediate configurations by acting differently on the various customization layers. Figure 2 shows a representation of the continuum of levels of AI systems' customization, highlighting the two extreme cases of "no customization" and "complete customization", along with the intermediate customization level.

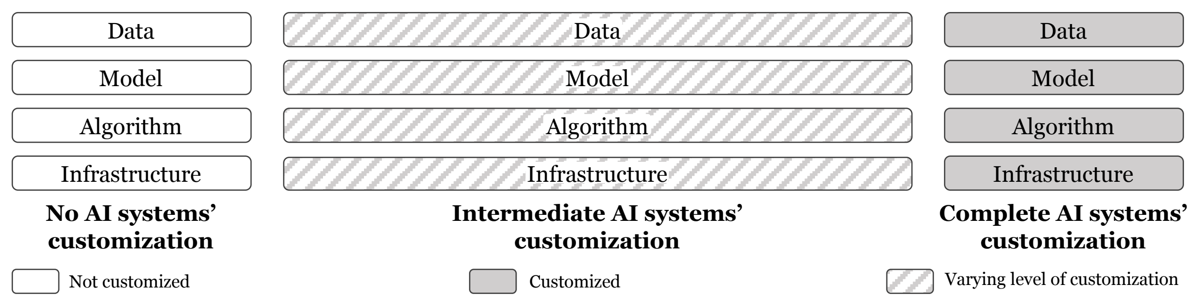

Figure 2. Levels of Customization for AI Systems

No customization entails the use of a standard AI system that only supports narrow use cases (e.g., automatic recognition of 50 types of images) sourcing a standard AI market product, without any adaptation to the business requirements of the organization. No further training data or tuning in terms of model, algorithm, or infrastructure are provided. In this case, the AI system simply relies on an AI product that creates new predictions through a standard embedded AI model. The Founder and CEO of a tech company operating in Financial Services made this example: "*companies are trying to streamline "Know Your Customer" procedures (KYC) through plug-and-play computer vision modules trained on extensive databases to verify identities through personal documents. Just find the right packaged service and go with it. You don't even need your own training data*". Similarly, our respondent from a European pharmaceutical company reported how "*platforms for laboratory data management are equipped with tools for the classification of tomographic images through standard computer vision capabilities*". In both cases, these AI systems support a narrow set of use cases without any need for customization. On the flipside, respondents highlighted that even if needs for customization emerge, AI systems sourced through standard market products with no customization parameters to set (e.g., standard APIs) often do not allow any customization at all, thereby failing to meet business requirements if these evolve.

At the opposite side of the spectrum, **complete customization** represents the highest possible level of customization and entails the setup of an AI system by acting extensively on all the layers of customization. Companies build new AI models based on their own training data and can develop new *ad-hoc* algorithms to meet internal requirements. In fact, as the Head of Data & Analytics at an IT company explained, companies might need to "*enter the mechanisms of algorithms to ensure the required flexibility and accuracy. Even standard Python libraries might not be enough*". Although some informants highlighted that this could be theoretically achievable also through a standard infrastructure (e.g., of a commercial cloud-based AI platform), we found that in all the cases part of this study, complete customization of AI systems also included some form of customization at the infrastructure layer. For instance, through the setup of "*a comprehensive architecture with all the non-AI components necessary for the final system to work*", as recalled by the Partner of a major IT consultancy.

While "no customization" and "complete customization" represent the two extreme levels, we found that companies can setup their AI systems with an **intermediate level of customization**, enabled by a variety of configurations. These intermediate options arise because of the varying degree to which companies decide to customize every customization layer. Although several configurations are virtually possible, we briefly present two examples of configurations emerged through this study. In a first configuration, companies implement their AI systems only thanks to the provision of new company-specific training data. This means that customization takes place only at the data layer by providing new training data to an AI product which has an embedded pre-trained AI model that only needs minimal additional training to increase performance for the desired use case and improve the scope of the use cases covered.

Since customization only entails acting on the data layer, companies do not act on the model layer (i.e., they do not compare and build models but rely on AI products with a single embedded underlying model), the algorithm layer (i.e., they do not come up with new algorithmic approaches but only rely on the standard algorithm embedded in the AI product), and the infrastructure layer (i.e., they rely on the standard enabling infrastructure of the AI product, without major adaptations). A second intermediate configuration emerged entails the use of company-specific training data to build new AI models either manually or automatically (e.g., through automated machine learning features) based on built-in standard algorithms supported by the chosen AI product. Compared to the previous case, this customization approach allows to seek a better match between a company's requirements and the AI system, as it allows to experiment with several algorithms and compare various models. Here, customization happens at the data and model layer, but the algorithm and infrastructure layers remain untouched. Examples include the use of commercial AI platforms through their guided tools, built-in algorithms and automated features, as in the case of a global leader in the metals and mining industry part of our study, that used this approach for quality assurance use cases. These two configurations within the intermediate level only represent two examples of the various ways in which companies can act on the AI customization layers to give rise to AI systems which fall more towards the "no customization" or the "complete customization" levels.

The Antecedents of the Level of Customization for AI Systems

We found that the choice of the level of customization for AI systems is linked to several characteristics of the company and the business problem targeted through the AI system. Specifically, we identified six antecedents of the desired level of customization, which are presented in Figure 3 as aggregate dimensions.

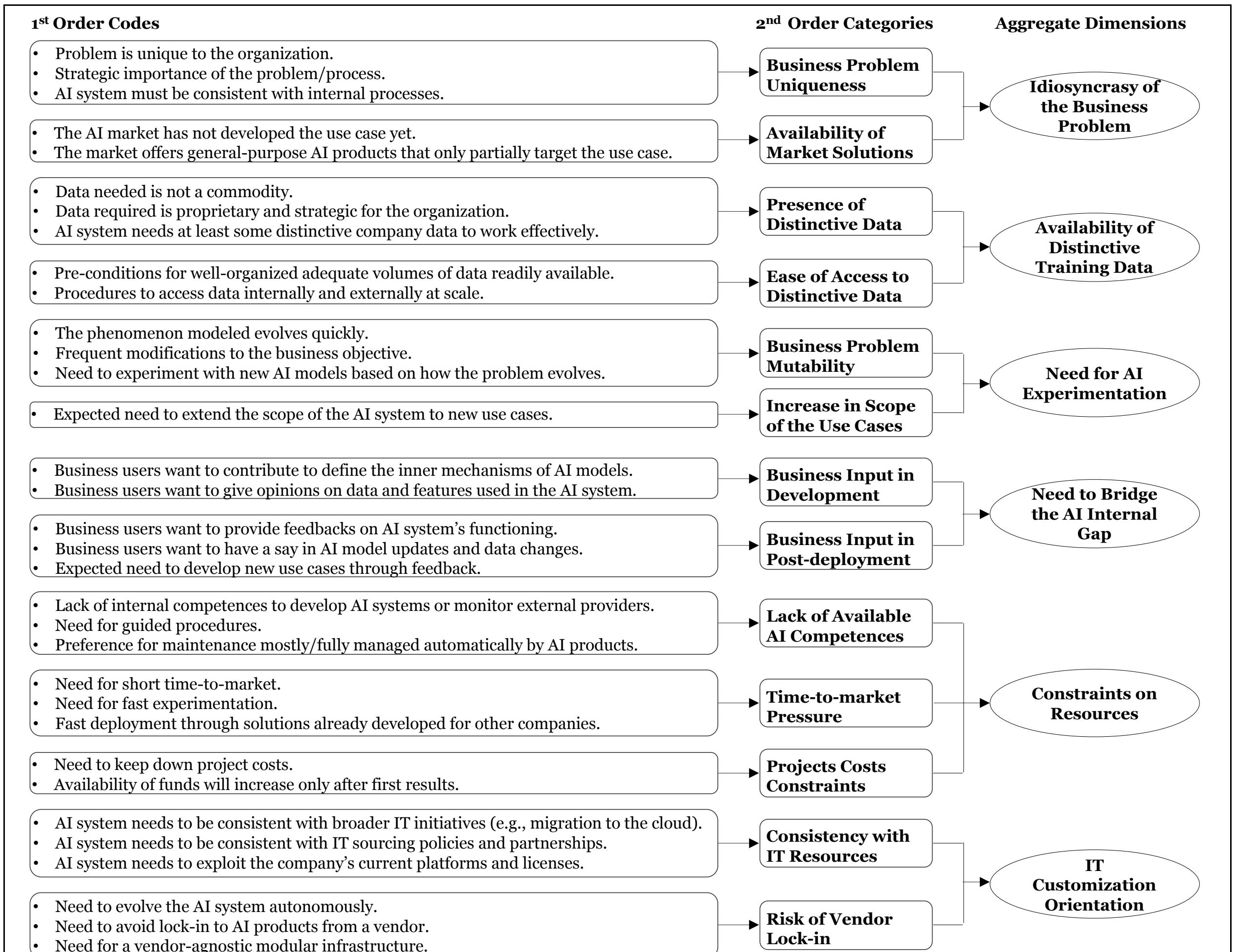

Figure 3. Coding Scheme for the Antecedents of the Level of Customization of AI Systems

Idiosyncrasy of the business problem expresses how specific the problem addressed with the AI system is to the company that implements the system. This determinant includes two complementary dimensions. First, an evaluation of how idiosyncratic and differentiating the business problem is compared to the rest of the market. As our informant from a major pharmaceutical company put it *"preclinical activities are highly company-specific, and every firm has its own research history. You need customized AI because you're touching how we create value, and you want to differentiate from competitors"*. Second, an assessment of the availability of external of AI products able to address similar problems with standard features. In fact, informants highlighted that in some cases, the market does not offer solutions that meet the minimal requirements that they need. This is consistent with a fast-changing but initial market for AI.

We found that the idiosyncrasy of the business problem impacts the desired level of customization because companies want to retain control over the inner mechanisms of AI systems and protect their know-how, as they perceive it as differentiating. Therefore, companies will likely act on a higher number of customization layers, providing proprietary data, customizing AI models, or even algorithms and infrastructures, as their requirements tend to be different than the ones of other players. For instance, when an IT company in our sample was working on an AI system to simulate epidemiologic trends for a new virus, market products could not address its need yet. Therefore, the firm had to enter the inner mechanisms of traditional AI algorithms and adapt them to the new application, thereby requiring a high level of customization. Contrarywise, if the problem is perceived as common to several other companies, firms fully exploit the standard features of the products that the market already offers. "*NLP pipelines are usually quite standard. We go to the market and look for the best product. We usually find many, as many industries face the problem of automating CRM*" recalled the manager in charge of Automation at a major energy company.

Proposition 1: A higher idiosyncrasy of the business problem determines a higher level of desired customization of the AI system. As the problem is likely to be a differentiating factor for the company, this pushes to act on more customization layers to ensure a match with company requirements.

Availability of distinctive training data expresses whether the company that is implementing an AI system has an adequate amount of distinctive data available for customization. First, there must be an adequate quantity and quality of data that are differentiating and not commonly available in the market to perform the customization. For instance, in the case of a virtual assistant developed at a major telco provider, our informant pointed out that "*at the beginning we only had limited data. We chose a well-known chatbot framework from AWS and only provided data for fine-tuning so that the bot could go live with two initial use cases. Only later, we could collect and clean more and more data and further customized the bot framework*". Second, if the company has differentiating data, such data needs to be readily available through adequate supporting infrastructures that allow to easily access the data at scale. For instance, when the Chief Digital Officer of a chemistry company first tackled a predictive maintenance project, he realized that "*it was a nightmare. All plants had their own systems, and it was so difficult to make those legacy technologies speak to one another that I gave up. I'm now working to build an enabling data platform to access data*".

When data are differentiating, of the right quantity and quality, and readily available, companies can provide new data to the AI system and pursue a better match between a generalist AI product and their requirements through the customization of, at least, the data layer. On the contrary, if this condition in not met, companies need to exploit either the standard features of an AI product without any customization or limit themselves to light configurations with the provision of limited initial data. For instance, in a computer vision task, if data are not distinctive or are not accessible, a company might be forced to use a standard computer vision API which supports the identification of a given set of objects but cannot provide any further data for customization.

Proposition 2: More availability of distinctive training data leads to a higher level of desired customization of AI systems. As the company has data that can increase the match between its requirements and the AI system, this pushes to the customization at least of the data layer.

Need for AI experimentation expresses how the company that is implementing an AI system expects the tasks targeted with the AI system to evolve over time, thereby requiring room for further experimentation with the AI system. This antecedent is composed of two dimensions. The first relates to the mutability of the targeted business problem, that is, how quickly the business problem changes due to shifts in objectives and how this impacts the need to update AI models. A Digital Project Manager at a

Spanish telco company explained that the company is exploiting an AI system to predict customer behavior and suggest commercial actions. However, "*our commercial offering changes quickly, and we always experiment with new promotions and sales options. We need to constantly provide new data and experiment with new models, compare them and see which one works*". We found that when the business problem addressed through the AI system evolves quickly, companies show a preference for being able to experiment with multiple models and evolve the model rapidly through new training data, thereby needing higher levels of customization.

The second dimension relates to the expected need to expand the scope of the use case addressed with the AI system. This need can make the search for a match between an AI market product and the company requirements more complex, as such requirements are expected to change and expand rapidly. An example is the use of standard AI products that only support narrow use cases and that do not allow any further training, which means that their configurability options do not even support low levels of customization. The standard features of these offerings might be enough at the beginning, but if the company already foresees that use cases will expand, it will be pushed to pursue solutions that support future experimentations. An AI Advisor at a global leader in metals and mining explained: "*we're starting from one case, but we know we'll need to expand it soon. Therefore, we're building an AI platform to input data, develop and test multiple models, deploy them for various use cases, so that every new one is a page of the same book*".

Proposition 3: A higher need for AI experimentation leads to a higher level of desired customization of the AI system. The use of AI to address a problem that evolves quickly and the expected expansion to other use cases makes requirements mutable, leading to the need for higher room for AI experimentations. This pushes towards customization of AI systems through the provision of new data and the training and comparison of different AI models.

Need to bridge the AI internal gap refers to the presence of a large gap between the technical and business sides regarding the understanding, perceptions and expectations about AI systems. When this is the case, internal business stakeholders need to be more directly involved during the development and after the deployment of an AI system to encourage integration into business processes. A key point raised by several respondents is that for AI systems to produce an actual impact, "*AI solutions need to really enter business processes. This means that people need to use them in their tasks*" as recalled the CIO of a telco company. Informants highlighted that a key driver for acceptance is their engagement throughout the process. During development, engagement takes the shape of "*creating communication between technical developers and business users with domain knowledge*", "*embedding domain knowledge into AI by considering relevant features and parameters*" and ensuring that "*workers understand and approve the impact of AI on their work*". After deployment, companies might need to "*allow business users to provide feedbacks on the functioning of AI*", be ready to use domain experts' feedbacks to decide "*when models need updates, and re-train models based on new data, even changing the underlying algorithms if needed*", as well as have the foundations to develop new use cases valuable to stakeholders if needed. For instance, in a virtual assistant project for an Italian banking institution, they started with an initial use case to troubleshoot some common problems with internet banking. Based on feedback from CRM operators and the analysis of conversations between clients and the virtual assistant, the technical team is now enlarging the AI system to streamline bank account openings. The retraining of AI models based on new data and domain experts' feedbacks is only possible if the company pursues at least a minimum level of customization.

Proposition 4: A higher need to bridge the AI internal gap leads to a higher level of desired customization of the AI system, as it requires a higher integration of domain knowledge, and feedbacks from stakeholders through the provision of data or the training and test of new models, pushing towards customization of, at least, the data layer.

Constraints on resources express the limitations of resources available for the implementation of the AI system. This antecedent entails three dimensions: competences, time constraints, and budget. The availability of AI competences refers either to the presence of internal competences to develop and maintain AI systems or the presence of resources to monitor the work of external providers. Competences constraints push companies to limit the level of customization, as high levels imply the need for competences that are not available to all organizations. As an AI Project Manager explained, "*we chose a well-known NLP* *solution where you only need to provide new texts to fine-tune the model. This is crucial since our client doesn't have AI technical skills*".

Time pressure and budget play a similar role. We found that if the pressure on time-to-market is high, companies tend to favor lower levels of customization, as they exploit as much as possible the standard features of AI products. The Partner of an AI company joked that some "*AI products are like frozen pizza. It's not like the real one, but if you're in a hurry, it does the job. When we need to build a proof of concept fast, we start from standard solutions with very limited configuration of parameters to show how the system could work*". Similarly, when there is high pressure to control costs and additional funds become available only after showing initial results, companies tend to prefer lower levels of customization to save time and resources, while customization could be pursued in a second phase if needed.

Proposition 5: Higher constraints on resources lead to a lower level of desired customization of the AI system. The lack of AI competences, time pressure and budget constraints push to exploit as much as possible the standard features of AI products, postponing potential customization to a later stage.

IT customization orientation expresses the general orientation of the company towards pursuing its objectives through a customized technology stack. We found that this antecedent is composed of two dimensions. First, companies choose a sourcing approach for AI systems that is consistent with their broader IT stack and initiatives. Informants highlighted that AI systems must be consistent with the current technology stack of the company, its existing partnerships, and the broader IT initiatives. For instance, an AI Management Consultant working on predictive maintenance recalled how they "*had to deal with old software licenses and partnerships that IT wanted to leverage. It was like a puzzle*". We found that this pushes towards a higher level of customization, impacting especially the infrastructure layer. On the contrary, the IT orientation can push towards standardization of IT infrastructures. For instance, if the organization embarked on a cloud migration program, "*the obvious choice will be to leverage the standard AI products offered by the same new provider"* confirms the Director of EMEA operations at a major automotive company. The second dimension relates to the perceived risk of vendor lock-in. We found that when companies perceive high risk, they tend to pursue higher levels of customization of AI systems by building enabling infrastructures that allow to keep a stable platform where to combine and evolve AI models from different sources. For instance, when a media and broadcasting company needed to *"remain independent",* they *"built a vendor-independent architecture where to integrate AI products from multiple vendors and open-source components*".

Proposition 6: A higher IT customization orientation leads to a higher desired level of customization of the AI system. An IT preference for customization and a high perceived risk of vendor lock-in push companies towards customization, especially at the "infrastructure" layer.

Figure 4 provides a summary of the presented antecedents and their relationship with the desired level of customization of an AI system.

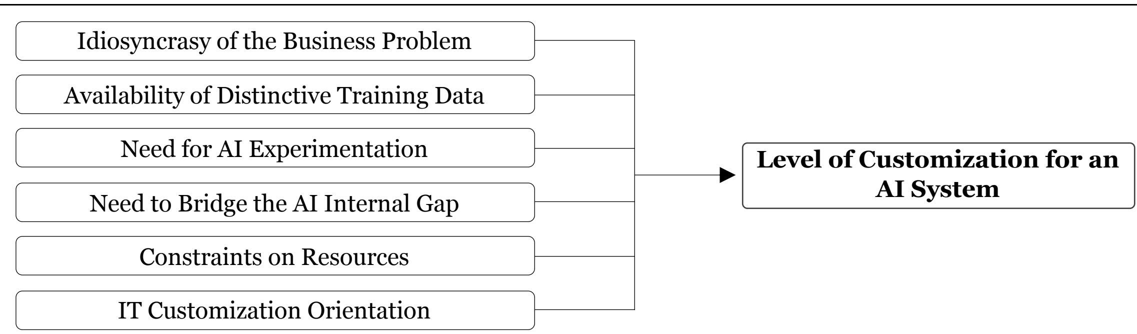

Figure 4. Antecedents of the Level of Customization for an AI System

Discussion

Research about AI systems continues to attract great attention, as demonstrated by recent calls to mitigate the complex challenges that surround the use of AI in companies (e.g., Berente et al. 2019; Benbya et al.

2021). In the vast field of IS, a key issue typically faced by companies is the decision of how to source their IS, pursuing the best fit between their characteristics and the features of software solutions in the market. IS customization emerged as a key means for organizations to mitigate a potential lack of fit (Gattiker and Goodhue 2005), which was recognized as a key factor for successful implementations (Xu and Brinkkemper 2007; Stefanou 2001). Despite the relevance of these topics for companies, little research explored the concept of customization in the context of AI systems, researching how different business characteristics impact companies' decisions regarding AI systems' customization. However, AI systems show several distinctive characteristics, which require to reexamine how established knowledge of IS translates to their context (Berente et al. 2019).

In this paper, we developed a conceptualization of customization for AI systems, grounded in their differences compared to traditional IS. Our conceptualization entails four layers that companies can decide to customize: data, models, algorithms, and infrastructures. This conceptualization also allowed to identify a continuum of levels of customization for AI systems, from "no customization" to "complete customization", which vary depending on how companies act on the four customization layers. Since we found that companies pursue customization to create systems in line with their business needs and constraints, we further explored such needs and offered a list of six antecedents, which influence the level of customization for AI systems desired by companies based on their business characteristics.

Theoretical Implications

Our work makes important theoretical contributions to two research fields: the field of managing AI systems and the field of customization of IS.

In the field of Managing AI (Berente et al. 2019), our work makes three important contributions. First, we introduce the perspective of customization of IS into the field of AI systems to explain the ways in which adopting companies seek a match between their requirements and AI systems, exploiting the variegated landscape of AI offerings, which provide different features in terms of configurability and complexity. Second, we offer a conceptualization of customization of AI systems grounded in the unique properties of AI compared to other IS. In fact, AI systems offer cognitive capabilities that go beyond the characteristics of traditional IS (e.g., Berente et al. 2021; Ransbotham et al. 2018; Li et al. 2021). These human or super-human capabilities are enabled by self-learning AI algorithms that learn from training data (Faraj et al. 2018; Li et al. 2021). Therefore, our work conceptualizes customization through customization layers consistent with these new and distinctive characteristics of AI systems. Third, we study how companies navigate their choices of customization, identifying a set of six antecedents that influence the desired level of customization based on their business needs and constraints. These contributions extend current research in the field of Managing AI and mitigate part of the challenges and uncertainties that still characterize the practical use of this technology in organizations (Berente et al. 2021).

This paper also brings three important contributions to the research field of the customization of IS by extending the current research debate. First, we introduce AI-based systems in the field of IS customization as a new class of software systems characterized by key differences compared to traditional IS. Second, we extend past knowledge about the concept of IS customization to this new class of software systems. Previous research on IS customization mainly focused on packaged software, enterprise applications, as well as cloud-based SaaS systems. The differences of AI systems compared to other types of IS (e.g., Berente et al. 2021; Ransbotham et al. 2018; Li et al. 2021) require a new conceptualization and an extension of the concept of IS customization. The distinctive characteristics of AI systems led to different levers that companies can use to customize AI systems. In the conceptualization of AI systems, the data, models, and algorithms layers are strictly related to the specific characteristics and functioning of AI systems compared to other IS, while the infrastructural layer relates to the enabling hardware and software elements that allow the AI system to function. Third, we build on previous typologies of IS customization developed in the fields of enterprise applications and SaaS solutions and provide a better understanding of the types of customizations that companies pursue for this new class of IS, organizing them in terms of different levels of customization. These contributions enrich the research field of IS customization by enlarging its scope to the pursue of a match between companies' requirements and the emerging field of AI systems.

Practical Implications

The results of our research can help companies that are evaluating the adoption of AI systems to make more aware and structured decisions on how to source them through the vast market of AI products offered by technology providers and the open-source world, while pursuing the best match between their needs and the features of such AI products. Specifically, we offer two contributions to practice. First, we contribute through the conceptualization of a continuum of customization levels for AI systems that can guide companies in balancing their needs with the efforts required for customization. This helps decision-makers to confront the variegated and confusing market of AI products with a clearer idea of where customization of AI systems can take place and how this relates to their needs. Second, we offer a comprehensive tool to support decision-making through a list of factors that companies can use to inform and guide their choice of the best level of customization for their AI systems, given their characteristics and business needs. These contributions provide valuable insights to professionals during the planning and implementation of an AI system, as they offer an actionable guide to rationalize the concept of customization and support in understanding how varying business and technical characteristics lead to different customization needs.

Conclusion, Limitations and Future Research

This paper explores the concept of IS customization in the domain of AI systems. We conceptualized AI systems' customization as a new concept grounded in the properties of AI compared to other IS explored in the past. We elaborated on how AI systems customization shows new and different connotations by identifying four layers where customization can happen: data, model, algorithm, and infrastructure. We identified a continuum of levels of AI systems customization, organized based on the layers where customization happens, ranging from no customization to complete customization. We showed that customization of AI systems takes the shape of configuration of available AI market offerings, or the creation of new AI systems based on enabling components from the commercial and open-source domains. To complete our analysis, we further identified six antecedents that influence the desired level of AI systems' customization for companies. We developed six propositions that show how higher levels of each of the identified antecedents impact the level of desired customization of the AI system. In doing so, we intersect two streams of previous research, the customization of IS and the emergent field of Managing AI. Our paper positions at the intersection between the two and brings a contribution to both fields. Our work is motivated by the need to reexamine previous IS knowledge in the new context of AI to shed light on the complex challenges and uncertainties that remain in the use of AI in companies (Berente et al. 2021).

Although our exploratory study provides first evidence on the concept of customization of AI systems and its antecedents, this paper features some limitations, which open the way to potential new studies. First, our results need to be further explored and replicated with other qualitative and/or quantitative studies to increase their generalizability. Second, this paper focuses on customization during the implementation phase of an AI system. Future studies could take a different perspective that dives into other phases of the lifecycle which are not addressed by this paper. Third, although our study identified four layers of AI systems customization and six antecedents, further analysis on the relationship between each antecedent and the single customization layers is needed to explore how high levels of each antecedent impact each layer of AI systems' customization. Fourth, future studies could refine the categorization of levels of AI systems' customization, identifying archetypes of customization that arise from different efforts on the various customization layers. Lastly, further research could explore the subject in a more process-oriented manner. This would help to shed light on the decision-making process that companies follow in their sourcing of AI systems to explore whether decisions on customization follow a process logic where the presence of some antecedents pushes to pass from one level of customization to the next.

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