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USE-CASE-BASED INNOVATION FOR ARTIFICIAL INTELLIGENCE – AN ONTOLOGICAL APPROACH

Research in Progress
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Abstract
Research has primarily focused on process models for AI-use-case-adoption, but neglected the use-cases themselves. In this research, an ontological artifact is developed as the basis for an AI-use-case-description-scheme. It allows practitioners and researchers to systematically describe such use-cases based on their level of abstraction and core characteristics. It enables them to classify, document and communicate these use-cases to support AI-adoption. We ground its development in diffusion of innovation theory and build upon research on AI-adoption. In particular, Rogers’ (2003) innovation decision process is utilised as a framework that explains adoption decisions by organisations. A Design Science Research approach is chosen that integrates the ontology development process by Noy and McGuinness (2001). In this research-in-progress, we conduct one ex ante and one ex post evaluation and plan for a second ex post evaluation that ensure the relevance and rigor of the artifact design.

Keywords: artificial intelligence, innovation, adoption, use-case, ontology

1 Introduction

One of the greatest technology-driven impacts in the past decade on business has been made by artificial intelligence1 (AI) as a general purpose technology (GPT) (Brynjolfsson & McAfee, 2017; Agrawal et al., 2019). It has disrupted production, commerce, innovation and other areas (Dwivedi et al., 2019). However, utilising AI to create new solutions poses a variety of challenges (Ransbotham et al., 2017), as it requires organisations to possess a range of resources and capabilities in order to be successful (Sturm et al., 2021; e.g. Hofmann et al., 2021). Several studies demonstrate the struggle of organisations to utilise AI in their businesses (e.g. Chui et al., 2018; Cam et al., 2019; European Union, 2019; WIPO, 2019; Brock & von Wangenheim, 2019). Which is – among others – due to some general challenges that are encountered when adopting AI: One is the lack of a general understanding of AI as a data-driven approach (AlSheibani et al., 2018; Hofmann, Jöhnk, Protschky & Urbach, 2020). Another is the lack of AI-resources (Ransbotham et al., 2017; AlSheibani et al., 2018; Cockburn et al., 2019) and -capabilities to innovate such solutions (Mikalef et al., 2018; Dwivedi et al., 2019; Duan et al., 2019; Hofmann et al., 2021), as well as a scarcity of general digital skill sets (Brock & von Wangenheim, 2019). However, organisations not only face technological and economic challenges, but also social, ethical, legal, data-related and organisational ones (Dwivedi et al., 2019).

The current range of tools to address these challenges are mostly suitable for organisations that already have some understanding of AI and have already embarked on the path of digital transformation (Brunnbauer et al., 2021; Spieth et al., 2021). Nonetheless, despite the effort of some research to demystify the opaque abilities of AI (Brock & von Wangenheim, 2019; e.g. Bean, 2019), the understanding of what AI is, when it should be used and how it can be implemented is described fuzzily in the practical realm (Dwivedi et al., 2019). In addition, the knowledge of how to create data-driven

1 In this research, AI refers to data-driven solutions (e.g. based on machine learning techniques), rather than knowledge-driven ones (e.g. expert systems), as understood in the WIPO-Report 2019 (Murphy, 2012; WIPO, 2019).
solutions with AI requires unique organisational capabilities on a technological, project management and social level (Tarafdar et al., 2019; Kugler, 2020). Especially organisations with little AI expertise lose track on the path to AI and thereby miss out on exploiting the opportunities this field offers (Chen et al., 2012; Brock & von Wangenheim, 2019; Borges et al., 2021).

The general purpose of AI does not make things easier for innovators and adopters. That is, organisations not only have to evaluate how well a new technology may solve a problem or fulfills a purpose, but have to identify the problems/purposes themselves (Hofmann, Jöhnk, Protschky, Stähle, et al., 2020). It is a common approach to address this challenge with what we call ‘Use-Case-Based Innovation’ (e.g. Sturm et al., 2021; Hofmann et al., 2021), which is primarily not about inventing the next disruptive breakthrough, but about adopting existing use-cases to solve a certain problem or to exploit an opportunity to create value. However, in addition to the general challenges named earlier, use-case-based innovation comes with its own AI-adoption challenges.

For example, it is not easily determined what the requirements for an AI-use-case exactly are (Hofmann, Jöhnk, Protschky & Urbach, 2020; Brunnbauer et al., 2021). Moreover, there is quite some effort in evaluating, to which degree an organisation is prepared for AI-based solutions. For instance, if the available data is actually sufficient, from a quality and quantity perspective (Price et al., 2018; Kruse et al., 2019), or if employees have the required acceptance for such solutions (Gursoy et al., 2019). In addition, organisations rightfully perceive their databases as unique (Provost & Fawcett, 2013, p.316; Iansiti & Lakhani, 2020), which makes it difficult to use pre-developed AI and especially machine learning (ML) models. This struggle with the uniqueness of databases was also confirmed in our expert interviews. These are key barrier to the adoption of AI-use-cases in several sectors, e.g. medicine (Shi et al., 2021) or manufacturing (Joppen et al., 2019).

Another challenge is that AI-projects are multi-disciplinary (Dwivedi et al., 2019), which require specific sets of capabilities to manage, e.g. technological and transformational capabilities (Mikalef et al., 2018; Dwivedi et al., 2019; Brock & von Wangenheim, 2019); For instance, when traditional products are combined with digital technologies, like AI, (Wang, 2021) to form product service systems (Meier et al., 2010). Furthermore, specifying the business value of an AI-use-case involves a lot of uncertainty (Pumplun et al., 2019; Demlehner et al., 2021), especially early in the innovation process (Borges et al., 2021). Our interview series (expert interviews), as well as screening practitioner publications (literature review), confirmed that there is a lack of detailed information on AI-use-cases within organisations and from what is available publicly about those use-cases (e.g. information on the investment costs needed to develop a prove of concept, data-quality measures, and others). Both methods demonstrate that an understanding of what a ‘use-case’ exactly is varies, which is further elaborated in section 2.1.

This study addresses these challenges and gaps by conceptualising use-cases and providing an ontology-based AI-use-case-description-scheme, through which such use-cases can be described for internal use, but also with external partners. The scheme supports practitioners in the adoption process on several stages: It allows organisations to systematically classify and document AI-use-cases (e.g. for analysis or reporting), it provides information on the respective use-case to support decision-making (e.g. to track decisions or overview design options), it facilitates the communication of use-cases in a structured manner to other stakeholders (e.g. to convince management or to transfer a use-case to another site). Organisations can thereby decide how much information about a use-case should be revealed.

A design science research (DSR) study (Hevner et al., 2004) is conducted to develop an ontology artifact (Noy & McGuinness, 2001) that supports practitioners in the five stages of the Innovation-Decision Process to overcome the discussed challenges (Rogers, 2003, p.169). The theoretical foundation of use-case-based innovation is further elaborated in section 2. The use of the DSR methodology and the ontological approach to develop the description-scheme is outlined in section 3. It covers the first two rounds of evaluation and describes the planned evaluations of the next iterations of this research in progress. We further describe the current version of the artifact in section 4. The paper ends with a conclusion of the current progress (section 5).
2 Use-Case-Based Innovation

The Innovation Decision Process (with its five stages: Knowledge → Persuasion → Decision → Implementation → Confirmation) (Rogers, 2003, p.169) can be split into two phases that overlap at the decision stage: First is the use-case-identification phase (Phase 1) (Cockburn, 1999, p.31; Vanauer et al., 2015; Jacobson et al., 2016; Hofmann, Jöhnk, Protschky, Stähle, et al., 2020; Brunnbauer et al., 2021; Sturm et al., 2021), followed by a use-case-implementation phase (Phase 2) (Dobing et al., 2010; Jacobson et al., 2016; Hofmann, Jöhnk, Protschky & Urbach, 2020). Existing literature has mainly focused on the incremental steps of these two phases, by suggesting different approaches for the identification of AI-use-cases (e.g. Brunnbauer et al., 2021), their development and evaluation (e.g. Hofmann, Jöhnk, Protschky & Urbach, 2020), as well as the selection of suitable AI-technologies (e.g. Collins & Williams, 2014). While these models suggest chronological steps for use-case-implementation – or parts of it –, there is little research that has developed tools to support these steps, in particular, the classification, documentation and communication of AI-use-cases. Consequently, the overall research question (RQ) of this study states: How can organisations be supported in the adoption-process of AI-use-cases?

To further divide this research question into sub-questions the following sections derive a conceptualisation of AI-use-cases (section 2.1) and the AI-adoption process (section 2.2).

2.1 Conceptualisation of AI-Use-Cases

To understand AI-solutions and -applications the concept of ‘use-cases’ is applied. The term has a much-unspecified use in practice and academia. In our interview study, for example, when presented with two different understandings of the levels of use-case abstraction, some experts said that a use-case is an abstract concept, which refers to approaches like predictive maintenance (PM) (see also Chui et al., 2018; Hecker et al., 2018). Others understood use-cases as a more concrete concept (see also Van Roy et al., 2021). For instance, they viewed PM as an application field of AI, because it can also be achieved with different technologies. From their perspective, ‘use-case’ refers to the concrete implementation of PM in a specified context: e.g., AI is used in the field of PM to provide a maintenance service from organisation A to organisation B, on machine Y, with data Z, etc. This bipartite understanding was further underlined during the review of practitioner publications.

Moreover, this is not only a phenomenon in practice. In research, the term ‘use-case’ has different uses, too, although it is rarely conceptualised in more detail. For example, authors conduct case-studies, in which the ‘case’ refers to the entity that is studied (e.g. an individual or a group), but it can also be more abstract (e.g. a decision or process) (Yin, 2018, p.73). At the same time, scholars often use the term ‘use-case’ to describe the application scenarios of technologies (e.g. Vanauer et al., 2015). In software development (SD), the term is used to refer to functional requirements for object-oriented software systems (Cockburn, 1999, p.2; Jacobson, 2005). In SD, Jacobson, Spence and Kerr (2016) have called for a Use-Case 2.0-concept that is not only suited to document or communicate solutions, but also to develop them. Tarafdar, Beath and Ross (2019) state that a use-case is defined by its application (what it does), the outcome it has for business, the users that are involved and the costs and benefits of it. Davenport and Ronanki (2018) propose that a use-case should be determined by the short- and long-term value it creates and the business success that comes from it. Amongst business scholars, researchers have stressed the importance of a clear problem statement and the business value for the adoption of an AI-use-case (e.g. Bremser et al., 2017; Pumplun et al., 2019). However, the core characteristics by which use-cases should be described are unclear. Especially when they are considered for a specific context, like a technology (e.g. AI, block-chain, etc.) or a defined sector (e.g. health, manufacturing, etc.). The first sub-question therefore states: What are the characteristics that describe an AI-use-case?

Among practitioners, the term is equally fuzzy. Sometimes ‘use-case’ refers to some very concrete application scenarios with defined context, specific goals of the organisation and selected technologies (e.g. Van Roy et al., 2021). For others, the term refers to a general application with unspecific context,
goals and technologies to be used (e.g. Chui et al., 2018; Hecker et al., 2018). For example, as mentioned before, PM is considered a ‘use-case’ in practice (Labbi & Ahmadi, 2021) and academia (e.g. Zoll et al., 2018; Masood & Hashmi, 2019). Others view it as an ‘important key’ to the operation time of a machine that can be solved through the combinations of various technologies, which depends on the concrete application (Carvalho et al., 2019). This specificity/abstractness of a use-case is partially accredited for by Demlehner et al. (2021), who consider ‘general use-cases’ in the automobile industry. They specifically identify use-cases that are enabled by AI, but are described on a general level, with no specific technology or KPIs. Their use-cases are mainly defined by the task they fulfil and the business value that is thereby obtained. This is different from a use-case that is clearly defined in terms of utilised technologies, specific goals measured by KPIs, the initial problem description and other characteristics that are relevant to someone who wants to learn about the use-case and potentially adopt it. To communicate the possibilities of AI within an industry (e.g. Chui et al., 2018; Hecker et al., 2018), a general use-case description might be sufficient. However, for an actual adoption decision, a more specific description is required that includes more details. The second sub-question therefore states: What are useful levels of abstraction for describing specific and general AI-use-cases?

A common facet of use-cases is that they are described by a clear problem or opportunity to manifest business value for the organisation. This is further considered hereafter.

2.2 Identifying and Adopting Use-Cases

Rogers (2003) distinguishes different types of organisations, from innovators to laggards, based on the invention and timing of adoption of an innovation (p. 267). We follow Rogers’ differentiation between innovators and adopters, but consider both types of organisations as innovating; either ‘new-to-the-world’/‘new-to-the-market’ (NttW) or ‘new-to-the-organisation’ (NttO), respectively (Booz & Hamilton, 1982; Olson et al., 1995). This study does not focus on a particular kind of innovation, like a product, a method, a process, a new business model, a service, etc. (Johannessen et al., 2001), but on the adoption of the use-cases that these innovations enable. As conceptualised before in section 2.1, use-cases are defined by a set of general, context-specific characteristics that describe them and the level of abstraction at which they are described. Moreover, a use-case can incorporate multiple innovations to solve a certain problem or exploit an opportunity.

In the case of AI and in line with Rogers (2003), Innovator-type (Type 1) and adopter-type (Type 2) organisations use fundamental technologies (e.g. machine learning), as well as market ready solutions. They differ, however, in the sense that Type 1 organisations tend to create NttW-use-cases (Fridgen et al., 2018; Hofmann, Jöhnk, Protschky & Urbach, 2020), while Type 2 organisations tend to adopt them (NttO) (Brock & von Wangenheim, 2019; Brunnbauer et al., 2021). At the same time, it is still possible for organisations to innovate NttW-use-cases, although they are mainly adopter-type organisations. Likewise, organisations typically of innovator-type can still choose to adopt existing use-cases. Hence, organisations have the option of two modes of innovation: innovator (Mode 1) or adopter (Mode 2). This is illustrated in Figure 1.

<table>
<thead>
<tr>
<th>Mode of Innovation</th>
<th>Organisation Type</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mode 1</strong> (innovator)</td>
<td><strong>Type 1</strong> (innovator)</td>
</tr>
<tr>
<td>A</td>
<td>Type 1 in Mode 1: (data-driven) Utilises its capabilities and resources to create new AI-use-cases.</td>
</tr>
<tr>
<td><strong>Mode 2</strong> (adopter)</td>
<td><strong>Type 2</strong> (adopter)</td>
</tr>
<tr>
<td>B</td>
<td>Type 1 in Mode 2: (business-driven) Is adopting and adapting existing AI-use-cases.</td>
</tr>
<tr>
<td>C</td>
<td>Type 2 in Mode 1: (data-driven) Does not have the capabilities and resources to create new AI-use-cases.</td>
</tr>
<tr>
<td>D</td>
<td>Type 2 in Mode 2: (business-driven) Is adopting and partially adapting existing AI-use-cases.</td>
</tr>
</tbody>
</table>

Figure 1. Approaches to utilising AI for innovation
Research on knowledge creation (e.g. Lewin & Massini, 2004) and new product development (e.g. Leonard-Barton, 1992) has argued that organisations with superior capabilities and recourses are more likely to create Ntw-innovations, although this must not lead to higher performance of the innovation (McEvily & Chakravarthy, 2002). More recent studies on digital technologies show that organisational capabilities, like the management of information or technological capabilities (Plechero & Chaminade, 2010), are facilitators of Ntw-innovations (Murmann & Zhu, 2021). Organisations with little of these resources and capabilities consequently tend to be in Mode 2.

It is difficult to pinpoint the exact capabilities that are required for successful AI-use-cases. Mode 1, as an more explorative approach, may require different resources and capabilities (Bremser et al., 2017) then Mode 2 (AlSheibani et al., 2018), although a range of them are likely to be similar for both modes. In the field of AI, a distinction is made through two types of approaches to AI-use-case development: data-driven and business-driven approaches (Vanauer et al., 2015; Hofmann, Jöhnk, Protschky & Urbach, 2020; Brunnbauer et al., 2021; Sturm et al., 2021). Authors supporting this distinction understand the term ‘data-driven’ as referring to an explorative, data-motivated manner. Meaning that depending on the available data, there might be some insights in that data from which a use-case may be developed. ‘Business-’ or ‘purpose-driven’ refers to an approach that is motivated by an opportunity for business value. We argue that data-driven approaches tend to align more with Mode 1, while business-driven approaches tend to align with Mode 2 (see Figure 1). This is because in an adoption scenario the use-case is usually already defined to a lesser or greater extent and includes at least a rough understanding of the business value it can provide (e.g. Demlehner et al., 2021).

This study partially – but not exclusively – addresses the innovation challenges for organisations in Mode 2, i.e. the ones adopting existing AI-use-cases (Taraifar et al., 2019; Brunnbauer et al., 2021).

3 Research Design

To develop an AI-use-case-description-scheme, this study takes a DSR approach (Hevner et al., 2004) using the process model by Sonnenberg and vom Brocke (2012) to focus on ex ante and ex post evaluations (Venable et al., 2016) of the artifact. An ontological approach proposed by Noy and McGuinness (2001) is chosen, as the artifact has the goal to define a terminology and structure to describe AI-use-cases. These authors suggest to first define the domain and scope of an ontology, which is in our case the domain of AI. The scope is specified by the purpose of the artifact, which is to create a description-scheme, through which AI-use-cases can be documented and communicated systematically. It also provides a taxonomic classification system (Noy & McGuinness, 2001) based on the characteristics of an AI-use-case.

The second step in ontology development is to consider existing ontologies, which is in line with our first ex ante evaluation/validation step, in which data is triangulated from two methods: First, 87 practitioner publications were collected from different intermediary organisations in Germany, Switzerland and Austria, such as industry associations, interest groups and private and public research organisations. In addition, reports and articles form international consulting organisations were included, as well. All publications were analysed to identify ontological artifacts, like AI-categories, typologies, classifications, scales and other dimensions, by which AI-use-cases and technologies are described and differentiated. This resulted in an initial coding tree. To complement the tree, AI-online community-based websites like huggingface.com and kaggle.com that were suggested by our interviewees were scanned and the codes adapted. This was a useful procedure, as these websites contain many insights into how communities view the field of AI.

As a second source of data, interviews were conducted with 22 experts (academic (7) and professional (8) researchers, consultants (5), AI-service providers (4) and AI-engineers (3) – some with a double role). In average, experts had 8.8 years of experience in the field of AI. The sample of experts covers a range of functional applications (WIPO, 2019, p.26), ranging from planning and scheduling to predictive analytics and natural language processing. Six of the experts work across different sectors. Ten are applying AI in industrial settings, four are specifically working in health and one is specifically
USE-CASE-BASED INNOVATION FOR ARTIFICIAL INTELLIGENCE

dedicated on insurance business. As the study follows an explorative approach, the interviews followed a conversational style (Flick, 2009, p.163; Sanchez, 2014) to adapt the topic of discussion to the direction of the interviewee. The guiding questions were thereby adjusted and placed at points of the conversation where they suited best to follow the natural flow of the conversation. The interviews were then transcribed and coded with the coding tree from the literature review. New (sub-)codes were added, if a statement did not match or fit into any of the existing codes. Through this triangulation, the problem statement was refined and validated. An initial structure was created for how – and by which dimensions and characteristics – to describe AI-use-cases.

In parallel, step tree of Noy and McGuinness (2001) development process was started, which is the enumeration of important terms in the ontology. This was already considered when the interview guidelines were designed. Therein, as an icebreaker question, experts were asked for the top five AI-related terms in their field. These are complemented by those from the coding tree.

After finishing the coding of the interviews, the coding tree was reworked into an ontology structure using the open-source tool ‘Protege’. On this basis, an expert evaluation (Peffers et al., 2012) was conducted by the means of a feedback form (Niehaves & Ortbach, 2016). The ontology is therein displayed to the experts and they are enabled to select the respective dimensions they want to evaluate. It contains the AI-use-case classes at different levels of abstraction and their characteristics that describe each class. The aim was to gain feedback on the relevance of the structure of the artifact and the characteristics it contains. This process is now repeated until experts agree at least on the general structure and characteristics. The feedback form is built based on the design principles derived by Niehaves and Ortbach (2016). This iteration corresponds to the process steps four to six in ‘Noy and McGuinness’ (2001) development process, in which the (sub-)classes are defined and the characteristics specified.

Thereafter, a third round of evaluation will be conducted, in which the description-scheme is applied on four concrete AI-use-cases in an action research approach (Iivari & Venable, 2009). Complementing the previous artificial evaluations, this naturalistic evaluation (Venable et al., 2016) is designed as an illustrative scenario (Peffers et al., 2012), in which the four organisations are selected to document their AI-use-case with the developed artifact. The main criteria considered for this evaluation are completeness, usefulness and ease of use according to Prat et al. (2015). Completeness is thereby defined as “the degree to which the structure of the artifact contains all necessary elements and relationships between elements” (p.266), usefulness as “the degree to which the artifact positively impacts the task performance of individuals” (p.266) and ease of use as “the degree to which the use of the artifact by individuals is free of effort” (p.266).

The results of this last round are likewise used to improve the artifact and future research may implement these results. This iteration corresponds to the final seventh step of ontology development, i.e. creating instantiations (Noy & McGuinness, 2001).

4 Description of the artifact

At the current stage, the artifact consists of the fundamental structure of the description-scheme in the form of a coding tree and an initial ontology prototype (Noy & McGuinness, 2001). It comprises multiple, individual, ontological artifacts derived from the data-triangulation. At the highest level the scheme is structured based on the factors of AI proposed by Dwivedi et al. (2019), namely technological, data-related, organisational, economical, legal, social and ethical factors (Due to the limited space for research-in-progress submissions, only the highest two levels of the ontology are presented and not every code is conceptualised and explained in full detail).

Technological factors contain the following codes: Use-case requirements, IT-infrastructure, machine learning (ML) approach, system architecture, model type, AI-function, AI-dynamics, openness, user/customer readiness. Some of these codes partially overlap with each other, which will be resolved in step 4 of ontology development, after coding is finished. For instance, the ‘use-case requirements’ characteristic is similar to the ‘IT-infrastructure’ characteristic, which is due to the use and
conceptualisation of these terms in both sources, literature and interviews. Moreover, characteristics like the ‘AI-function’ (optimising, generating, predicting, reasoning, etc.) can be arranged in a matrix with the ‘ML approaches’ (supervised, unsupervised and reinforcement learning), as some of these are particularly suited for each other. For example, supervised learning is well suited for predicting-AI and reinforcement learning is well suited for acting-AI.

Data factors contain the codes ‘data structure’ (structured, unstructured), ‘data life-cycle’, ‘data processing location’ and ‘data storage location’. These cover the data-dimension of AI-use-cases that is deeply entangled with other factors, such as data-privacy or ethics, when it comes to personal data, but also with regard to the AI-technologies that can be applied.

Organisational and managerial factors comprise the ‘AI development process’, the ‘application context’, the ‘use-case goals’, the ‘project time frame’, and the ‘motivation for adoption’. In particular, the concepts motivation, goals, aims, problem statement and opportunity have to be conceptualised to ensure a uniform use of them when describing AI-use-cases with the artifact.

Economic factors mainly focus on the KPIs that are used to measure the success of an AI-use-case. We differentiate general KPIs and context specific ones that are often unique for a certain use-case.

At the current stage political, legal and policy factors, as well as social and ethical mainly comprise intellectual property related characteristics and focus on human-in-the-loop-AI.

5 Conclusion

Although several studies have considered the adoption process for AI-use-cases (e.g. Pumplun et al., 2019; Sturm et al., 2021), few studies have addressed the issue of classifying, documenting and communication such use-cases. This was also confirmed by our interview study with AI-experts from academia and practice, who stated that it is difficult to find detailed information about specific AI-use-cases. This is a key adoption barrier, as such data-driven projects come with many uncertainties, ranging from data-availability (Price et al., 2018; Kruse et al., 2019) to business value assessment (Pumplun et al., 2019; Demlehner et al., 2021).

An ontology-based AI-use-case-description scheme could build the basis for the classification, documentation and communication of AI-use-cases, organisation-internal and -externally, depending, for example, on what information about a use-case is approved for public sharing. However, the description-scheme has to include relevant information that can be utilised by the multi-disciplinary teams that conduct AI-projects (Dwivedi et al., 2019). Our approach to triangulate data from practitioner publications and expert interviews provides an initial structure for this description-scheme, which we develop in this DSR study (Hevner et al., 2004). In line with DSR methodologies, additional ex post evaluations are conducted to refine our artifact.

At the current stage, we were able to validate and refine the initial problem statement to meet the relevance for the users. However, it is likely that our 22 interviews, with specific focus on the health and industrial sector could not cover all facets of AI-sue-cases sufficiently. We try to address this limitation by evaluating the completeness of the description-scheme, which may expose further dimensions and characteristics that can be covered by future research. An additional limitation is that the utilised multidisciplinary dimensions by Dwivedi et al. (2019) require additional experts from research fields on AI that are underrepresented in our study. For example, the interview study included only two experts with a background in ethics. Future research could cover these dimensions specifically, which would also require stronger human centred approaches.

Acknowledgements

This research is partially conducted in the context of the project IIP-Ecosphere, funded by the German Federal Ministry of Economic Affairs and Climate Action (BMWK). Funding code: 01MK20006F
References


USE-CASE-BASED INNOVATION FOR ARTIFICIAL INTELLIGENCE

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VAN ROY V, ROSSETTI F, PERSET K and GALINDO-ROMERO L (2021) AI Watch - National
strategies on Artificial Intelligence - A European perspective. Luxembourg, Belgium.


