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Artificial Intelligence in Energy Demand Response: A Taxonomy of Input Data Requirements

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Abstract. The ongoing energy transition increases the share of renewable energy sources. To combat inherent intermittency of RES, increasing system flexibility forms a major opportunity. One way to provide flexibility is demand response (DR). Research already reflects several approaches of artificial intelligence (AI) for DR. However, these approaches often lack considerations concerning their applicability, i.e., necessary input data. To help putting these algorithms into practice, the objective of this paper is to analyze, how input data requirements of AI approaches in the field of DR can be systematized from a practice-oriented information systems perspective. Therefore, we develop a taxonomy consisting of eight dimensions encompassing 30 characteristics. Our taxonomy contributes to research by illustrating how future AI approaches in the field of DR should represent their input data requirements. For practitioners, our developed taxonomy adds value as a structuring tool, e.g., to verify applicability with respect to input data requirements.

Keywords: Energy Informatics, Green IS, Demand Response, Artificial Intelligence, Input Data Requirements

1 Introduction

Due to the expansion of renewable energy sources (RES) and their inherent variability, ensuring security of supply and grid stability are becoming increasingly challenging [1]. A successful energy transition towards growing shares of RES largely depends on increasing energy system's flexibility [2–4]. To achieve this, demand needs to be adapted to generation, instead of the other way around. In order to actually provide and foster energy system flexibility, research develops and reflects several approaches of Artificial Intelligence (AI) algorithms for Demand Response (DR) to enable flexibility

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on the demand side. As subset of Demand Side Management (DSM), DR focuses on load shifting or shedding and reacting to external signals such as price signals from the energy market [40–42]. To enable a broad application of algorithms in the real world, in general data are the "key ingredients" [5]. It is especially important that requirements on input data match the actual data availability and accessibility. However, the approaches of AI algorithms for DR typically lack an analysis of their actual real-world applicability with respect to input data requirements of algorithms, e.g., data accessibility or data type. Hence, we aim to gain applicable knowledge by identifying gaps that need to be addressed in terms of input data requirements in order to successfully apply AI algorithms in the field of DR.

As our paper is located at the interface of renewable energy systems and digitalization, the basis of our work is particularly formed by the following two research streams, which are growing and becoming increasingly important in Information Systems (IS) research: (1) AI and (2) the role of IS for a more sustainable world. Regarding (1), AI's breakthrough within the last years emerged with the increasing availability of large amounts of data (Big Data) and growing computing capacity [6, 7]. This resulted in an increased interest in and relevance of AI and corresponding algorithms, which play a major role in many industries [8]. Also, research reflects that in the field of IS, AI is receiving greater attention and creates new information and knowledge at the intersection of business and technology [9]. Regarding (2), a growing number of IS researchers is increasingly getting aware of their responsibility for sustainability [10, 11], especially with respect to the energy transition, for more than a decade, constituting the fields of Green IS and Energy Informatics (EI) [10–13]. More recently, the research community calls for applicable solutions for a green energy system by reflecting IS's role of transferring research into practice [14–17].

In order to cope with the intermittent feed-in of RES, research emphasizes the important role of flexibility for years [18–20], also with a focus on respective IS applications [21]. Therefore, incentives to actually increase flexibility of the energy system are gaining importance [22]. Several types of flexibility exist, such as supply-side flexibility, storage flexibility, transmission flexibility, demand-side flexibility, and inter-sectoral flexibility [23]. In particular DSM and – more specific – its subset DR play a major role as DR is a key element to enable short-term changes in energy consumption behavior [22, 23]. [24] analyze various AI approaches in the field of DR by conducting a literature review. In analogy to [24], we use the term AI algorithms as we analyze algorithms in the areas of machine learning, nature-inspired intelligence, artificial neural networks, and multi-agent systems. The review by [24] underlines the high relevance of AI algorithms for DR while providing a comprehensive overview of different application areas of algorithms. However, the authors do not analyze the (practical) applicability of AI algorithms. Particularly apparent is the absence of an analysis concerning the input data required for the algorithms. The lack of such data would actually impede the applicability of the DR algorithms. Hence, the aim of our research is to provide the necessary foundation for moving AI in DR to application stage, and therefore, to promote applicable solutions in the context of the energy transition. Therefore, we consider AI approaches within DR from an IS-perspective and analyze, how to systemize required input data for AI approaches in the area of DR. Our objective is to demonstrate which input data requirements algorithm developers need to account for in order to achieve applicability. Hence, we pose the following research question:

What are the main characteristics of input data requirements in the context of AI algorithms for DR?

In line with [25], we aim to build theory for analyzing the DR algorithms' applicability by developing a taxonomy as a systematization of input data requirements. Hence, future approaches related to AI algorithms for DR may describe their input data requirements in the form of our taxonomy, allowing for an easy comparison and applicability analysis. In addition to providing a theoretical conceptual basis for research, we enable practitioners with a tool for structuring and comparing to evaluate AI algorithms for DR in terms of required input data.

To approach our research question, this paper is organized as follows: In the second section, we briefly introduce the research streams of Green IS and EI [20]. Further, we introduce the conceptual basis and related work concerning IS-enabled flexibility, input data requirements of AI approaches for DR and data taxonomies. In the third section, we then outline the paper's research methodology, i.e., the taxonomy development method according to [26]. In the fourth section, we elaborate on the application of this research method for our research question. We then present our developed taxonomy, systematizing input data requirements of AI approaches in the DR area in the fifth section. Building on this, the sixth section contains the contribution of the paper. Finally, the seventh section draws main conclusions and summarizes the paper.

2 Theoretical Background

This section forms the theoretical background for our analysis and presents related work. We reflect the following relevant research areas step-by-step: (1) Green IS and EI, (2) data taxonomies, (3) IS-enabled flexibility, and (4) input data requirements of AI approaches for DR.

Regarding (1), in academic literature, researchers increasingly emphasize the responsibility of IS for environmental sustainability [10, 11]. This has led to the development of a new core subfield of IS, called Green IS [27–29], which signifies the use of information and communication technology to foster the transition to sustainable economies [11]. EI is one research field of Green IS and according to [14], EI focuses on increasing energy efficiency and integrating RES effectively and "has evolved into a thriving research area within the IS community" [14]. [15] and [13] stress that EI aims to reduce energy consumption and associated greenhouse-gas (GHG) emissions. In order to develop a more sustainable energy system, also an increase in flexibility is particularly necessary [2, 30]. One approach to achieve increased flexibility is DR. Therefore, this paper aims to contribute to the EI and Green IS research streams in line with its approach of investigating the applicability of AI algorithms for DR. Since Green IS represents an "applied field that seeks to improve practice" [11], applicability is of highest importance to gain applicable knowledge. In the field of EI, [31] explicitly stress the aspect of lacking data, which also highlights the importance of our work for

IS research, as we develop an approach to examine the input data requirements of the algorithms that are important for applicable solutions. Since this specific field of research is still quite new, a taxonomy from a methodological perspective lends itself to structuring the field.

Regarding (2), taxonomies are already well established in the IS domain, especially since Nickerson et al. (2013) presented a taxonomy development method specifically for the IS domain [32]. IS researchers apply taxonomies in different IS areas, but generally all of them are used to classify and group objects and accordingly to structure, understand, and analyze complex domains [33]. Holistic taxonomies regarding data already exist in literature. [34], for example, present a general taxonomy of data, based on, e.g., the statistical approach and the source of data generation, while [35] develop a taxonomy of data sources including dimensions such as data source interface or data source pricing model. [36] evolve a taxonomy in the area of data-driven business models used by start-ups including dimensions such as data source, but also key activity or target customer. These examples illustrate the relevance of taxonomies for structuring data and data requirements for specific application areas. Yet these taxonomies cannot represent the input data requirements in the field of DR, because the taxonomies presented serve different purposes and accordingly exhibit other dimensions and characteristics. DR is a special area at the interface between energy systems and many other fields, such as industrial production planning or residential applications, e.g., electric vehicles. Thus, e.g., a more general and holistic view on data requirements of energy systems would not be sufficient for our purpose. Overall, already existing data taxonomies cannot be used for an accurate and applicable systematization of AI algorithms for DR.

Regarding (3), as mentioned above, flexibility is crucial for a stable and efficient energy system [23, 37]. Against this background, one approach to increase flexibility is *DSM*, which includes all measures on the consumption side of the energy system, such as increasing efficiency as well as reducing energy consumption [38]. [39] emphasizes that DSM aims to influence energy consumption in order to achieve beneficial changes in the load profile. As a subset of DSM, *DR* is defined as load shifting or shedding and reacting to external signals such as price signals from the energy market on demand side [40–42]. Regarding DR in IS-literature, [41] summarize general IS research contributions on DR by conducting a systematic literature review. [21] use a real options analysis to quantify the value of IS-enabled flexibility on demand-side and illustrate this analysis with electric vehicles. [30] develop an approach for industrial consumers to evaluate DR measures by analyzing the risk transfer capability of flexibility performance contracts. So far, in the IS literature, DR researchers have not focused on AI to govern DR. Therefore, we build on and contribute to the research stream of DR in IS literature by systematizing input data requirements of AI approaches for DR to improve their applicability in practice, and thus increasing flexibility in the energy system. In this way, our paper serves as a foundation for further research by contributing to the interface of AI algorithms and DR.

Regarding (4), with its plethora of application areas, AI opens up opportunities for the energy industry and the energy system [43]. In general, AI "attempts not just to understand but also to build intelligent entities" [44]. Hereby, AI encompasses a variety of different techniques such as machine learning [45], that enables agents to intelligently perform tasks. For the applicability of AI algorithms, required input data plays a major role, as IS literature clearly demonstrates: [46], for example, highlight that data availability, data quality, data accessibility, and data flow are main factors for organizational AI readiness and are therefore crucial for applicability. In addition to that, [5] emphasizes that "data are the key ingredients of all machine-learning systems" [5]. By analyzing and evaluating data sets, AI helps the energy system to become more efficient and secure. In the energy system, various AI application areas exist, ranging from energy trading and sector coupling to smart grids. In this context, [47] elaborate on the general use of AI in energy systems and energy markets, while [48] focus on AI applications that can support the achievement of RES future goals. For instance, regarding specific AI applications used for smart grids, [49] as well as [50] provide a detailed overview of AI applications for smart grids such as stability assessment, stability control, security assessment, and fault diagnosis. Our paper focuses on the applications of AI in the DR area. In this context, AI is especially used for load and price forecasting, scheduling and control of loads, design of pricing and incentive schemes, as well as load and customer segmentation [24]. However, the basis for a real-world application of these AI approaches, i.e., appropriate input data, remains unstructured, so far.

To put it in a nutshell, general AI literature is concerned about data requirements of respective algorithms, while researchers in the field of AI for DR have not yet paid particular attention to the analysis of necessary input data. However, in order to be able to truly apply AI algorithms in the field of DR in practice, an analysis of these input data is essential. Against this background and to the best of our knowledge, we are the first taking a more in-depth view of the input data required by AI algorithms for DR.

3 Methodological Approach

To answer our research question, we develop a taxonomy as a systematization for input data requirements of AI algorithms for DR. According to [26], such classification of objects is particularly helpful for researchers and practitioners to understand and analyze complex domains. A further objective of taxonomy developments is to lay the foundation for future research and simultaneously provide new and highly relevant impulses [51].

The guidelines of [26] are based on the approach of [52] and are well known in the IS discipline [53–56]. According to [26], the structured and iterative taxonomy development process encompasses seven steps, combining an inductive (empirical-to-conceptual) and deductive (conceptual-to-empirical) approach [26]. The first step is to identify a meta-characteristic (1), which should reflect the purpose of the taxonomy. Subsequently, in the second step, one defines ending conditions (2), which determine when the iterative process terminates, differentiating between objective and subjective ending conditions. The third step allows the decision between the empirical-to-conceptual, in the following denoted by an (e), or the conceptual-to-empirical approach, in the following denoted by a (c) (3), depending on the availability of data about the objects. Following Nickerson's guidelines, it is useful to perform different approaches in the iterations "to view the taxonomy from a different perspective" [26]. When applying the empirical-to-conceptual approach, [26] suggest to select objects for classification (4e) first, then to identify common characteristics of these objects (5e), and finally to group these characteristics into dimensions (6e). When employing the conceptual-to-empirical approach (3), [26] suggest to first conceptualize the dimensions and characteristics of the taxonomy (4c), then to map objects to the characteristics and dimensions (5c), and finally to create the new or revised taxonomy (6c). Both, the empirical-to-conceptual and the conceptual-to-empirical approach require an examination whether the current taxonomy fulfills the objective and subjective ending conditions (7). If these are not met, a new iteration starts, otherwise, the taxonomy development terminates.

4 Application of the Research Method

Figure 1 illustrates our methodological process, which consists of determining meta-characteristic and ending conditions followed by five iterations comprising three empirical-to-conceptual approaches and two conceptual-to-empirical approaches.

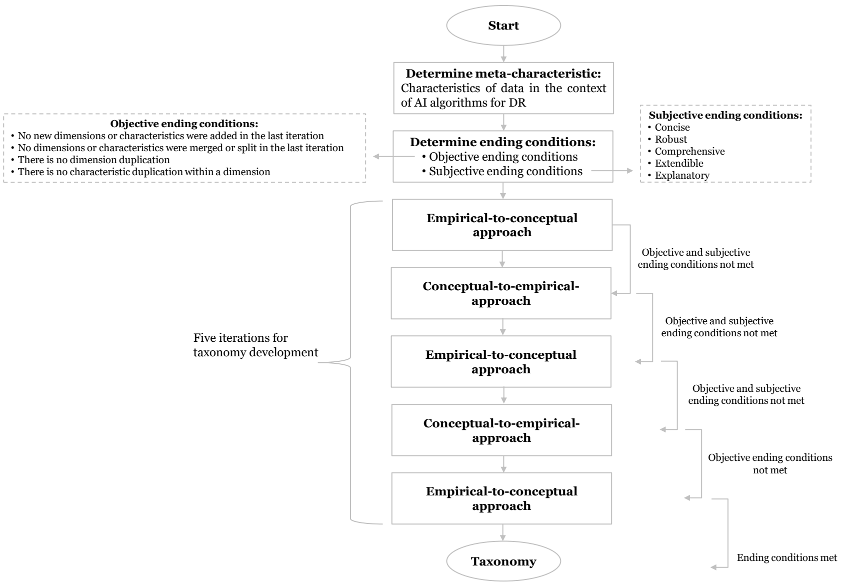

Figure 1. Taxonomy Development Process Adopted from Nickerson et al. (2013)

The first step of the taxonomy process requires the definition of the *meta-characteristic*, from which all characteristics and dimensions of the taxonomy must logically derive [26]. Based on our research question and the corresponding target group of the taxonomy - researchers and practitioners dealing with AI for DR - our metacharacteristics are characteristics of input data in the context of AI algorithms for DR (1). Next, in a second step, we define the ending conditions that determine the termination of the taxonomy development process (2). As *objective ending conditions* we choose the following: “no new dimensions or characteristics were added in the last iteration” [26], “no dimensions or characteristics were merged or split in the last iteration” [26], “there is no dimension duplication” [26], and “there is no characteristic duplication within a dimension” [26]. For the *subjective ending conditions*, all authors have to confirm that the taxonomy is concise, robust, comprehensive, extendible, and explanatory [26].

We develop a taxonomy with eight dimensions encompassing 30 characteristics and two additional requirements in five iterations by combining the empirical-to-conceptual (first, third and fifth iteration) and conceptual-to-empirical approach (second and fourth iteration) as described above. For the *first iteration* - an empirical-to-conceptual approach (3) - we use a sample of 15 algorithms as objects. These are part of the result of a systematic literature review (SLR) by [24], which meets the requirements of a SLR according to [57]. The conducted SLR uses the search strings “Artificial Intelligence” AND “Demand Response”, “Machine Learning” AND “Demand Response”, and “Neural Networks” AND “Demand Response”. [24] only consider literature that is DR-related and that uses AI techniques explicitly for DR. The applied search engine is Scopus and it searches the period from 2009 to 2019 [24]. 15 algorithms are, according to [26]’s guidelines, randomly selected as objects from the 161 SLR results. First, we investigate the input data requirements of the algorithms by reading the corresponding 15 papers in detail (4e). Subsequently, we form characteristics concerning input data requirements from these objects (5e) and group them into dimensions to create a first taxonomy (6e).

Since the resulting taxonomy does not meet both, the subjective and objective ending conditions, we perform a second iteration. To view the taxonomy from a different perspective, we now perform a conceptual-to-empirical approach (3). To follow the guidelines from [26], we use the “knowledge of existing foundations, experience, and judgement [from the authors] to deduce […] [further] relevant dimensions” [26] and characteristics (4c). We can learn from other data taxonomies mentioned in the second section in this conceptual-to-empirical approach and strengthen our taxonomy by, e.g., adopting single characteristic names for more general dimensions like data source or data accessibility. Subsequently, we examine 15 new objects from the above-mentioned SLR for these new characteristics and dimensions (5c) and create the revised taxonomy (6c) [26]. Similar to the first iteration, we add new characteristics and dimensions, and therefore, the taxonomy does not fulfill the objective ending conditions. Consequently, we carry out a *third iteration*. In this empirical-to-conceptual approach (3), we examine 15 new objects from the SLR with respect to differences and similarities (4e). Since our taxonomy does not meet the subjective and objective ending conditions, we perform a *fourth iteration*, a conceptual-to-empirical approach. As already mentioned in the second iteration, according to [26] we can use the knowledge and experience of the authors to further develop the taxonomy. In *iteration five*, we neither add new dimensions nor new characteristics [26]. We check the objective and subjective ending conditions. All objective ending conditions are met and the authors separately review the subjective ending conditions concluding that they are fulfilled as well [26].

5 Taxonomy

Our final taxonomy comprises eight dimensions encompassing 30 characteristics and two additional requirements. We define the taxonomy according to our meta-characteristic with the aim to systematize input data requirements of AI algorithms for DR. Table 1 illustrates our final taxonomy. In the following, we explain all dimensions and characteristics of the taxonomy, and give substantiating sources.
In order to be able to apply AI algorithms for DR in practice, the data used as input plays a decisive role: Our taxonomy illustrates that the input data requirements differ, especially with respect to the eight dimensions data usage, data type, data provider, data collection time, data source, method of data collection, data accessibility, and data privacy, which we amplify in the following.

Table 1. Taxonomy of Input Data Requirements in the Context of AI Algorithms for DR (in dark grey further input data requirements are shown)

<table>
<tr><th>Dimensions</th><th colspan="12">Characteristics</th></tr>
<tr><td>Data usage</td><td colspan="3">Forecasting</td><td colspan="3">Scheduling and control of loads</td><td colspan="3">Design of pricing and incentive schemes</td><td colspan="3">Load and customer segmentation</td></tr>
<tr><td>Data type</td><td colspan="2">Genera-tion data</td><td colspan="2">Price data</td><td colspan="2">Grid data</td><td colspan="2">Consum-ption data</td><td colspan="2">Weather data</td><td colspan="2">Geograph-ical data</td></tr>
<tr><td>Data provider</td><td colspan="2">Generator</td><td colspan="2">Trading operator</td><td colspan="2">Grid operator (TSO/DSO)</td><td colspan="2">Consu-mer</td><td colspan="2">Meteoro-logical institute</td><td colspan="2">Building industry</td></tr>
<tr><td>Data collection time</td><td colspan="3">< 1 month</td><td colspan="3">1 month < 6 months</td><td colspan="3">6 months < 1 year</td><td colspan="3">≥ 1 year</td></tr>
<tr><td>Data source</td><td colspan="6">Internal data</td><td colspan="6">External data</td></tr>
<tr><td>Method of data collection</td><td colspan="6">Primary data</td><td colspan="6">Secondary data</td></tr>
<tr><td>Data accessibility</td><td colspan="4">Open data</td><td colspan="4">Shared data</td><td colspan="4">Closed data</td></tr>
<tr><td>Data privacy</td><td colspan="4">Free and usable data</td><td colspan="4">Corporate secrets</td><td colspan="4">Personal data</td></tr>
<tr><td>Data quality</td><td colspan="12">Data quality is a crucial precondition to obtain reasonable results.</td></tr>
<tr><td>Data granularity</td><td colspan="12">The spatio-temporal data granularity is dependent on the data type and application.</td></tr>
</table>

Based on the analysis of the reviewed objects and in line with the overview of AI for DR by [24], we differentiate between four application areas, representing the characteristics for the dimension **data usage**: The first characteristic *forecasting* includes approaches for load forecasting [58–60] as well as for energy price forecasting [61, 62]. There are differences with respect to short-term and long-term forecasts [24]. While short-term forecasts allow consumers to better respond to price signals and aggregators to provide better services, long-term forecasts provide useful information to better plan DR measures. *Scheduling and control of loads* constitute the second characteristic. Here, we note that significantly more algorithms are developed at the consumer level [63–65] than at the aggregator level [66, 67], especially with the aim of reducing energy costs and energy consumption [24]. Another characteristic of data usage comprises the *design of pricing* or *incentive schemes*, which both affect the success of the DR scheme [68–72]. These compensation mechanisms are important for a successful DR program [24]. The final characteristic in this dimension describes *load or customer segmentation*, the categorization of energy consumers in groups which is predominantly based on consumer load profiles and supports, e.g., designing DR programs [73, 74]. Our taxonomy development process revealed that AI algorithms for DR operate on a number of **data types** to meet the specific goals of the algorithms. Characteristics of the dimension data type include *generation data, price data, grid data, consumption data, weather data, and geographical data*. A majority of them represent the components of the electricity system value chain [1]. Examples for *price data* comprise real-time price data [62] or day-ahead price data [75]. Real-time data from sensors and dynamic data sources [76] or 15-minute interval meter data [77] represent examples of *consumption data*. Furthermore, we form the characteristic *geographical data* based on the objects' data such as building construction [76] or type of heating appliances [77]. When examining objects during the taxonomy development process, it is notable that various **data providers** exist for the AI algorithms in the DR domain. Our taxonomy groups these stakeholders into the characteristics *generator* [78], *trading operator* [79], *grid operator* including transmission system operator (TSO) and distribution system operator (DSO), *consumer*, *meteorological institute*, and *building industry*. In our taxonomy, the data provider refers to the stakeholder that makes the data available, but who not necessarily generates it. In addition to the above dimensions, the length of the **data collection time** is important for the applicability of AI algorithms for DR. Only if the data is sufficiently available for the relevant period, the user can properly apply the algorithm. The objects imply a subdivision in *< 1 month* [80], *1 month < 6 months* [81], *6 months < 1 year* [82], *≥ 1 year* [83] as characteristics for the dimension data collection period. The underlying data differs in their source. In line with literature, **data sources** can either be internal or external [36]: *Internal sources* comprise data that is self-generated or data that already exists, e.g., when data is stored in IT systems [84]. In contrast, *external data* is generated publicly or can be purchased [35]. Examples of external sources include acquired data, e.g., from EPEX SPOT, data provided by customers, or freely available data, e.g., from the international energy agency [84]. Regarding the **method of data collection**, we identify the requirement of converted input data in some objects [77], whereby we distinguish between primary data and secondary data [34]. *Primary data* are raw data and are directly gathered from the source by the algorithm user itself, while *secondary data* are not collected by the algorithms' user and may also be edited, derived, and processed. We underline the fact that the method of data collection must be distinguished from the data source. For example, in the case of primary data, the data does not necessarily have to be produced internally, but rather requires that it is not processed prior to its use. Regarding the **data accessibility**, we find essential differences between the objects' input data. In line with literature, we differentiate between open data [85], shared data [86], and closed data [76]. *Open data* is free and available to anyone for unrestricted commercial or non-commercial use and may be shared without restriction [87]. *Shared data* is accessible to users who meet specific access criteria and indicate the source of the data whenever they use it [34]. Regarding *closed data*, access is restricted to the data owner or a special group due to security restrictions and policies. Additionally, data cannot be shared with third parties. In order to also consider privacy rules, **data privacy** ought to be an input data requirement and thus forms a dimension in our taxonomy. Data privacy focuses especially on the use and governance of individual data. One example is establishing policies to assure an adequate manner, in which personal data is collected, shared, and used [88]. In this context, there is a need for balancing of civil liberties and societal interests. In addition, regulations regarding data privacy like, e.g., General Data Protection Regulation (GDPR) differ depending on the country in which the algorithm is applied. We distinguish between free and usable data, data that companies keep secret due to the protection of corporate secrets, and personal data. Several of the objects' developers also emphasize the need to pay attention to data security to avoid revealing unwanted details about people and their activities [76] as well as privacy protection [89]. In addition to the dimensions mentioned, two **further input data requirements**, namely data quality and data granularity, are essential for systematizing the input data requirements of AI algorithms for DR. However, compared to the above dimensions, these two requirements do not entail specific characteristics and cannot be classified as a dimension in the sense of [26]. According to [26], characteristics must be “mutually exclusive and collectively exhaustive” [26]. Since no specific characteristics can be defined for data quality and data granularity, it would not be assured that each object has a characteristic in the dimension data quality and data granularity. Therefore, we list these two separately in the form of further input data requirements in dark grey in Table 1 and describe them afterwards. Even if data is available, good **data quality** is crucial. As data quality can be seen gradually, we do not directly include data quality in the taxonomy, but we list it as an extra input data requirement of AI algorithms for DR. Since many IS-researchers are already concerned with data quality required for an algorithm to produce “good” results, we will not focus on this issue in more detail. However, it is crucial to consider data quality as one of the input data requirements. Data quality attributes include, for example, ensuring that the data is free-of-error, meaning that the data is accurate and reliable, and completeness, which is intended to assure that no data is missing [89, 90]. The algorithms' developers also mention missing data quality: [91], for instance, note "some data were missing in the database" [91] and "some data is not accurate" [91]. Similarly, **data granularity** can be seen gradually: The right granularity is a crucial precondition to obtain reasonable results in the first place. Besides, the dimension of data granularity is highly dependent on the data type and also on the application. Therefore, it is not possible within our research to specify generic characteristics for the dimension of data granularity. In particular, different units hamper generic definitions of characteristics for the data granularity dimension. For example, price data have a different granularity than generation data.

6 Contribution and Discussion

In the field of Green IS and EI, researchers emphasize the responsibility of IS for a sustainable and more efficient energy system [10, 11, 13]. In addition, [92] highlight the importance of research on IS-enabled energy flexibility. In this context, our paper first contributes to the Green IS research stream by building a foundation to raise awareness among researchers and also algorithm developers to place a deeper focus on the applicability of AI approaches in the field of DR in terms of data requirements. Applicable knowledge and implementable practices are especially important in the field of Green IS and EI to foster a successful energy transition and to address the UN SDGs [15]. By focusing on input data, we address a major topic in algorithm development, as the availability of the required input data is crucial for the actual applicability of the algorithms. While literature contains various AI algorithms for DR, so far, it does not deal with their real-world applicability sufficiently, i.e., the analysis if input data requirements of these algorithms match the actual data available. Our paper illustrates that different data usage, data types, data providers, data collection times, data sources, methods of data collection, data accessibility, data privacy, data quality, and data granularity exist for various AI algorithms. Second, with our taxonomy we lay the foundation for AI algorithm developers and researchers in DR to illustrate the appropriate characteristics of each dimension of our input data requirements taxonomy in their future AI for DR approaches. Henceforth, papers developing an algorithm at the interface of AI and DR may present their input data requirements in the form of our taxonomy. This provides the advantage of "easier" analysis of applicability and "simpler" comparison of AI algorithms for DR in terms of their input data requirements. Third, our developed taxonomy can serve as a conceptual basis for future research in this field, by giving an overview of input data requirements of AI algorithms for DR. For example, our taxonomy provides a basis for analyzing which combinations of input data requirements typically occur in different application areas. In addition, our taxonomy forms the basis and is the first step towards analyzing which data is needed for AI algorithms in the area of DR and should be provided with an open data license, taking into account ethical and privacy concerns. In addition to that, our taxonomy can serve as a starting point to investigate which other currently licensed and closed data types could play an important role for AI algorithms in the area of DR.

Besides the theoretical added value, the results of our paper also have several practical implications that play a major role for promoting the energy transition [11]: In order to apply AI algorithms for DR in practice, practitioners need to know the algorithms' input data requirements for implementation of the algorithms.

First, the taxonomy provides practitioners of AI algorithms for DR with a manifold overview of which input data and corresponding characteristics respective algorithms may require. Second, for practitioners who apply AI algorithms in practice, our taxonomy further serves as a structuring tool. For the identification and selection, but also for the evaluation of an algorithm with respect to the input data requirements, the taxonomy represents an important tool: By analyzing algorithms based on the characteristics of the taxonomy, practitioners can evaluate whether they are actually able to apply the algorithm or not with respect to required data. Third, building on such evaluation, users of AI algorithms for DR can apply our taxonomy as a tool for comparing. Here, the focus is on the comparison of different algorithms and their respective input data requirements. Accordingly, practitioners can also use the taxonomy to identify advantages and disadvantages with respect to the required input data in a structured way. Fourth, our taxonomy may enable new business models by serving as an assistance for companies that sell relevant data. Our taxonomy allows to identify which specific input data is required for AI algorithms in the field of DR. Based on such information, companies can consider publishing relevant data with an open data license, or alternatively sell the data on a data market.

7 Conclusion, Limitations, and Further Research

To put highly relevant AI approaches into practice, referring to Section 6, we present a systematization of the input data requirements of AI algorithms for DR by developing a taxonomy following the process of [26]. The final taxonomy consists of eight dimensions, which are data usage, data type, data provider, data collection time, data source, method of data collection, data accessibility, and data privacy as well as 30 characteristics. Furthermore, we highlight data quality and data granularity as further input data requirements for AI algorithms in the area of DR.

Having laid out our results, we briefly present some limitations of our work. First, already [26] note that a taxonomy "is never perfect, but in the best case useful" [53]. Regarding this citation, our taxonomy development is limited to findings from academic literature. Second, as the AI application field is rapidly evolving, the taxonomy should remain regularly updated, and depending on new (scientific) development, new input data requirements may extend the taxonomy in the future. Third, we illustrate that our taxonomy serves its purpose and yet, we are aware that this taxonomy is only the first step towards the real-world applicability of AI algorithms for DR. Fourth, an evaluation of the taxonomy through expert interviews is outstanding, which is in turn the starting point for our further research.

Our paper provides various starting points for further research. Referring to the limitations, in a next step, researchers can conduct a reality check and validate the taxonomy through expert interviews. Researchers may also apply our taxonomy to classify actual AI algorithms for DR. Moreover, our taxonomy may serve as a starting point for cluster analysis, for example, to develop archetypes and patterns for AI algorithms in the field of DR. These archetypes and patterns may provide a basis for identifying certain gaps in existing AI algorithms for DR and for deriving further research priorities. In addition, further research can examine how data granularity and data quality can be further characterized. Also, an overview of characteristics of the sampled and evaluated AI methods with respect to the taxonomy could help to prove further relevance and applicability of the taxonomy. Besides, it would further be useful to practitioners who need to choose a method for their problem.

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