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# Moving Beyond Rule-Based Automation: A Method for Assessing Cognitive Automation Use Cases

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# Moving Beyond Rule-Based Automation: A Method for Assessing Cognitive Automation Use Cases

*Completed Research Paper*

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## Abstract

*Facilitated by Artificial Intelligence technology, cognitive automation means to front and back offices what the pervasive automation through physical machinery and robots meant to production plants. Thus, we can automate tasks and processes that were unimaginable to be automated one decade ago. However, organizational adoption of cognitive automation is way below its possibilities, as this novel class of automation technology is perceived to be risky by organizations. This demands structured approaches for assessing the suitability of use cases for cognitive automation. Following the Design Science Research paradigm, we develop a method for assessing cognitive automation use cases. This enables practitioners to make more informed decisions on selecting, specifying, and embedding cognitive automation use cases in their organizations. For researchers, the method serves as a conceptual frame, which they can adapt to guide their empirical research or to use it for developing future decision support to shape the future of work.*

**Keywords:** Cognitive automation, use case, assessment, method, future of work

## Introduction

Facilitated by AI technology (AIT), cognitive automation (i.e., learning-based software robots) extends the scope of deterministic automation – e.g., robotic process automation (RPA) – through the probabilistic automation of knowledge and service work (Coombs et al. 2020; Drucker 1993). To front and back offices, this development compares to what the pervasive automation through physical machinery and robots meant to production plants. Cognitive automation aims at automating or augmenting tasks and processes seizing Machine Learning (ML) algorithms that facilitate processing structured and unstructured data, leading to probabilistic outcomes (Butner and Ho 2019; Lacity and Willcocks 2018a). Accordingly, nowadays, we can automate tasks and processes that were unimaginable to be automated one decade ago, such as deploying voice or chatbots for handling customer requests, performing automated criticality screenings of contractual agreements, detecting fraud in customer interactions, or translating written or spoken language. This largely impacts the future of work as we know it. Thereby, organizations are provided with novel strategic opportunities to gain business value (Coombs et al. 2020). This potential has been well recognized in practice. 75 percent of technology and operations executives state in a survey among 550 participants to expect it to have "meaningful impact on their business performance" (Butner and Ho 2019, p.25). However, so far only 26 percent of potential adopter organizations state to have particular systems in place, which is rooted in the still comparably high price of CA tools, the required amounts of data, and the insecurity of organizations due to the unpredictability of outcomes of this novel class of automation technology (Lacity and Willcocks 2018b). This demands structured approaches for assessing the suitability of potential use cases for cognitive automation.

If organizations select a task or process that is not suited for automation, the endeavor is likely to fail (Bachrach 1997; Leshob et al. 2018). In this realm, recent research on assessing the suitability of automation use cases in front and back offices has been mainly driven by rule-based automation, i.e., robotic process automation (RPA) (Syed et al. 2020). However, due to the novel class of cognitive technologies being deployed, traditional assumptions of automation research such as that "[m]ore procedural or predictable tasks are handled by smart machines, while humans have become responsible for tasks that require inference, diagnoses, judgement, and decision making" (Militello and Hutton 1998, p. 1619) do not hold anymore. Therefore, we problematize that against the backdrop of changing assumptions regarding the phenomenon of cognitive automation, there is a lack of methodical support in assessing the suitability of use cases for cognitive automation (Alvesson and Sandberg 2011). Thus, in this paper we pose the following research question (RQ):

***RQ:*** *How can IT decision makers be supported in assessing the suitability of cognitive automation use cases in a structured manner to decide on whether and how to deploy them in their organizations?*

To answer this RQ, we follow the Design Science Research (DSR) paradigm (Alan Hevner et al. 2004), and develop a method artifact for assessing cognitive automation use cases. We report on a 2-year DSR journey of iteratively developing the method artifact, in which we applied a hybrid of deductive and inductive knowledge creation strategies using an exterior mode of theorizing (Baskerville et al. 2018). In that, we draw on the existing IS knowledge base and account for the novelty of the phenomenon of cognitive automation through analyzing empirical case data from corporate reality as well as applying the method artifact in action research settings (Baskerville 1999). The method consists of nine steps, which we complement with a set of existing tools from research and practice. Furthermore, we develop own tool support (e.g., standardized set of assessment questions, IT-based scoring model etc.) to tailor the method to the specifics of cognitive automation.

Overall, our method enables practitioners to make more informed decisions on selecting, specifying, and embedding cognitive automation use cases in their organizations. Furthermore, the method serves as a basis for developing diagnostic tools and services. For researchers, the method artifact shall serve as a structural and conceptual frame, which they can adapt or extend to both guide their empirical research or to use it as a foundation for developing future decision support for cognitive automation support to shape the future of work. This shall contribute to enriching the IS knowledge base on factors and steps affecting the adoption of cognitive automation, which deepens the understanding of the phenomenon of cognitive automation in particular, and AI in general.

# Conceptual Foundations of Cognitive Automation

AI, which is facilitated by technological advancements in algorithms, computing power, and data storage during the last decades (von Krogh 2018), offers novel ways of automating business processes, using ML as today's most prevalent instantiation of AI (Janiesch et al. 2021). AI can be considered as a superordinate phenomenon including machines performing existing tasks and/or processes, producing decisions and/or solutions. AI comprises any technique that facilitates machines to mimic human behavior and reproduce or excel over human decision-making to solve complex tasks independently or with minimal human intervention (Russell and Norvig 2021). We limit the scope of this paper to narrow AI rather than Artificial General Intelligence (AGI) (Gubrud 1997). Narrow AI is an AI that is equally as good or better than a human in a specific domain of tasks, while in contrast an AGI would be considered equally as good or better than a human in any domain of tasks (Gubrud 1997). ML is the technical implementation of narrow AI and its sub phenomena and refers to a computer program's performance improving with experience with respect to some class of tasks and performance measures (Jordan and Mitchell 2015).

Lacity and Willcocks (2018a) refer to cognitive automation in the following notion: cognitive automation refers to automating or augmenting tasks and processes seizing inference-based algorithms in order to process structured and unstructured data leading to probabilistic outcomes (Lacity and Willcocks 2018a).

We build up on this definition and propose an integrated definition relating the concepts of AI in general and ML in particular by emphasizing their conceptual relationships and scope.

Thus, from an integrated perspective, cognitive automation refers to seizing ML for automating cognitive knowledge and service work to realize value offered by AI, which is based on implementing artificial cognition that mimics and approximates human cognition in machines.

Against this backdrop, cognitive automation targets the area of knowledge and service work (Coombs et al. 2020) and thus necessarily involves the automation of information and control in order to decrease the need for human intervention (Bruckner et al. 2011). As pointed out in the introduction of this paper, this is impacting front and back offices in the manner physical machinery and robots have impacted production plants. However, in the field of cognitive automation as well as RPA, we are faced with software robots rather than physical robots (Hofmann, Samp, et al. 2020). While RPA relies on so-called rule-based software robots that operate according to predefined rules, cognitive automation relies on so-called learning-based software robots that seize Machine Learning to develop experience from data (Kroll et al. 2016). To clearly position cognitive automation and delineate it from deterministic approaches in the field of software robots (Hofmann, Samp, et al. 2020; Kroll et al. 2016), we delineate cognitive automation from RPA in further detail while pointing out their highly complementary relationship. RPA refers to "using software to automate tasks previously performed by humans that use rules to process structured data to produce deterministic outcomes" (Lacity and Willcocks 2018a, p.24).

Robots in RPA represent software agents that can mimic user actions in order to interact with software systems, thus reducing the workload of human agents (Syed et al. 2020). RPA is usually applicable to the automation of routine tasks, which occur in high volume at a low level of complexity and are usually performed by humans (Zarkadakis et al. 2016). Cognitive automation tools such as IPsoft's Amelia or IBM's Watson are different in that they can "use natural language interfaces to read, build patterns, and relationships among data, and apply knowledge to solve problems or pose additional pertinent questions" (Lacity and Willcocks 2018a, p.26). Thus, machine perception has been found to be a prerequisite of cognitive automation (Bruckner et al. 2011) as cognitive automation shall mimic human activities such as perception, inferring from data, developing hypotheses, and reason upon them to perform judgment-intensive tasks (Rainey et al. 2017). As this requires action supported by context in a manner of human rationale (Poosapati et al. 2018), cognitive automation uses AI technology (AIT), mostly in the manner of Machine Learning (Butner and Ho 2019; Lacity and Willcocks 2018a). Thus, cognitive automation is facilitated by machines that perform cognitive functions, which are typically associated with humans, including perceiving, reasoning, learning, and interacting (Rai et al. 2019).

# Related Work

The question of what should be automated and what should be done by humans is not new (van der Aalst et al. 2018). If organizations select a task that is not suited for automation, the endeavor is likely to fail, which demands structured approaches for assessing and selecting tasks to increase the likelihood of success (Bachrach 1997; Leshob et al. 2018). Thus, researchers have investigated the selection of suitable automation candidates. For instance, earlier automation research already used expert systems (Waterman 1986) or knowledge-based systems (Blount et al. 1995) to achieve automation goals but however faced high project failure rates during that time due to poor task selection (Blount et al. 1995). Thus, to select the right tasks for automation, talking to subject matter experts of the particular task, and thorough investigations of economical and technical dimensions of automation projects were approached (Prerau 1990). Furthermore, assessment criteria were introduced such as feasibility, technological appropriateness, and justification (Waterman 1986). Building up on this, researchers introduced methods considering more fine-grained task characteristics, such as task complexity (Sintchenko and Coiera 2003), distinguishing routine versus non-routine, and manual versus cognitive tasks (Autor et al. 2003), or by analyzing required skills such as perception and manipulation, creative intelligence, or social intelligence (Frey and Osborne 2017).

Recent IS research on selecting automation candidates has been driven by the emergence of RPA during the last years. New methods have been developed to select suitable automation candidates for RPA (e.g., Leshob et al. 2018). These methods build up on assessment criteria developed for these purposes. RPA is recommended when levels of standardization, maturity, transaction volume, and existence of business rules are all high (Lacity and Willcocks 2018a). According to other criteria, rule-based routine tasks with few exceptions, and little or no cognitive reasoning are most suitable for RPA (Asatiani and Penttinen 2016). Based on this, tools have been developed to support the assessment of suitable automation use cases for RPA, for instance by seizing process mining software (Geyer-Klingeberg et al. 2018).

In the realm of assessing AI and Machine Learning use cases, recent work has developed methodical support, which largely emphasizes the explorative phases of use case generation at a general AI level.

Guided by Osborn's (1953) divergence-convergence dualism, Sturm et al. (2021) draw on a qualitative study with 24 experts to explore the process of problem finding for AI solutions, which results in a framework for problem finding in AI. It poses an initial step in problem-solving activities with AI and particularly emphasizes the explorative identification of AI use cases through ideation and evaluation of problems. Their procedural framework consists of the phases of data- or purpose-driven ideation, evaluation of problem substance for general Machine Learning Suitability (hard factors) and evaluation of problem particularities, which are soft factors specific to a problem's particular context (Sturm et al. 2021).

In a similar vein, Hofmann et al. (2020) use DSR and situational method engineering to develop a five-step method for developing purposeful AI use cases. According to their method, companies must first consider the context factors technology, organization, and environment, before in a next step they can collect existing domain problems and AI solutions, which are abstracted in a third step (Hofmann, Jöhnk, et al. 2020). In a fourth step, Hofmann et al. (2020) introduce a problem-solution matrix to help companies match AI functions with problems, before in a fifth step, companies derive implications use case implementation.

Overall, we can summarize that selecting the right automation use cases constitutes an essential step in deciding on automation endeavors and has attracted attention from both researchers and practitioners. However, as cognitive automation moves beyond rule-based automation, we face a different degree of richness in the scientific knowledge base. We argue that the methods and sets of criteria developed for rule-based automation (see above) do not cover cognitive automation as it is a phenomenon of perceiving, reasoning, and inferring, which is rooted in the probabilistic character of AIT following different logics than deterministic approaches such as RPA. Furthermore, in this paper, we build up on existing research in the realm of AI and Machine Learning (e.g., Hofmann et al. 2020; Sturm et al. 2021). We extend it by purposefully focusing on the phases following the exploration of general AI use cases. In cognitive automation, the divergent phases such as exploration and ideation of potential use cases are less emphasized than in cases with a broad general AI scope, which also cover AI-based innovation or decision-support. This is because cognitive automation uses existing tasks and processes as a starting point for respective projects, which results in a smaller solution space. However, this does not mean that reengineering processes or tasks can be neglected in assessing cognitive automation use cases. In that, we seek a level of abstraction, which shall facilitate organizations to conduct in-depth assessments of particular tasks or processes to being performed by cognitive automation systems. Thus, we develop a method for assessing cognitive automation use cases that is tailored to this novel phenomenon through its methodical structure and set of assessment criteria.

# Methodology

First, we describe our research goal and endeavor in the light of the Design Science Research (DSR) paradigm, before we elaborate on our two-year DSR journey of designing a method for assessing cognitive automation use cases.

## *Positioning the Research Endeavor in the Design Science Paradigm*

In IS research, DSR has become an established research paradigm for the construction of socio-technical artifacts (Gregor and Hevner 2013), which follows the philosophy of design as a search process seeking utility (Hevner et al. 2004). Against this backdrop, the artifact can be considered as an axis of cohesion in DSR that serves as a guiding theme during this search process. Research defines different types of design artifacts: in particular constructs, models, methods, and instantiations (March and Smith 1995). In order to develop and instantiate a method for assessing cognitive automation candidates that exhibits value and usability in terms of conceptual content and structure to both researchers and practitioners, we thus seize the DSR paradigm (Hevner et al. 2004) for guiding our overall research endeavor. We briefly describe our research design along the characteristic DSR dimensions (Engel et al. 2019) of "outcome" (Gregor and Hevner 2013), "build" (Baskerville et al. 2018), and "evaluate" (Venable et al. 2016).

**Outcome:** The intended outcome of this Design Science endeavor is a method artifact. In that, "[a] method is a set of steps (an algorithm or guideline) used to perform a task" (March and Smith 1995, p. 257). Our method of assessing cognitive automation use cases shall pose a nascent level-2 design theory, which we complement with a situated implementations of the method, i.e., instantiations in a manner of tool support and method inputs (Gregor and Hevner 2013). This shall act as an improvement in terms of its knowledge contribution (Gregor and Hevner 2013).

**Build:** To achieve this outcome, this DSR project uses a hybrid of deductive and inductive knowledge creation strategies applying a mix of interior and exterior modes of theorizing (Baskerville et al. 2018). In the deductive vein, we draw on the existing IS knowledge base thus creating a methodical and conceptual repository in iterative rigor cycles (Hevner 2007) seizing existing literature (Webster and Watson 2002). In the inductive module, we intend to enrich our understanding of the particular context of assessing cognitive automation use cases by drawing on interviews with practitioners from the field. This relevance cycle (Hevner 2007) shall assure us to identify a set of relevant use case assessment dimensions. These dimensions are essential building blocks of the method and shall guarantee its organizational relevance. To base these on a rigorous scientific basis, they are assessed against the existing knowledge base (rigor cycle). To orchestrate the method components in terms of organizing the concepts such as assessment dimensions derived from the interviews and literature in a structure (set of steps), we draw on a nine-month Action Research project together with a large manufacturing corporation. The project is carried out according to the Action Research cycle - (1) diagnosing, (2) action planning, (3) action taking, (4) evaluating, and (5) specifying learning (Baskerville 1999). The goal is to apply and iteratively refine the method artifact in a naturalistic setting actually impacting organizational decision-making on whether to select a certain use case for cognitive automation or not. Afterwards we let two student teams apply the method in two three-month Action Research projects to further refine the method.

**Evaluate:** The purposeful coupling with the organizational context is also reflected in our evaluation strategy that shall assure attaining a method artifact that is relevant, rigorously designed, and usable for both research and practice. Thus, the dominant evaluation strategy to test and refine the artifact can be described as naturalistic and formative by seizing iterative steps of refinement before a summative evaluation of the final method artifact is conducted (Venable et al. 2016).

## *A Two-Year Journey of Design Science Research*

Figure 1 provides an overview of the nine distinct phases of our two-year DSR journey. We note here that researchers investigating the mission of DSR in IS research agree on the duality of contributing to both theory and practice. However, they face an inherent trade-off in achieving both relevance and rigor.

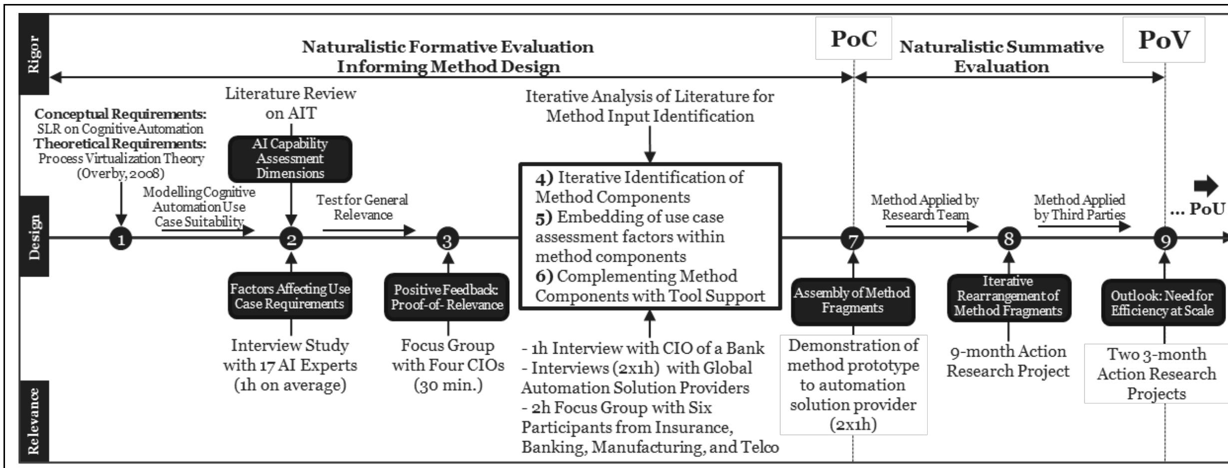


**Figure 1. Two-Year DSR Project**

Against this backdrop, Nunamaker et al. (2015) call for achieving both relevance and rigor in DSR endeavors and propose the concept of "the last research mile". According to Nunamaker et al. (2015), the last research mile consists of three research steps that aim at solving the dilemma between rigor and relevance: (1) proof-of-concept (PoC) research, (2) proof-of-value (PoV) research, and (3) proof-of-use (PoU) research. Hereby, PoC research identifies a relevant problem and shows the feasibility of a solution alternative from a technical perspective. PoV research intends to empirically show the efficacy of a solution in lab and field studies to allow for judgement of the potential value it creates in the real world. PoU research demonstrates ongoing usage and acceptance of a solution in the community of users, which completes the last research mile.

Against this backdrop, we describe the nine DSR phases of intertwining rigor, relevance, and artifact design.

To build our method on a conceptually sound and theoretically grounded foundation of rigor (*DSR phase 1*), we first draw on an SLR to establish a deeper understanding of the phenomenon of cognitive automation and derive structural requirements informing method design from Process Virtualization Theory (Overby 2008). Process Virtualization Theory guides the development of our method in a manner of a kernel theory, i.e., conceptual lens and structural guideline. The theory explains the transition from a physical process to a virtual process in the light of IT (Overby 2008). In that, the theory seeks to explain to which degree processes are suited to being migrated into virtual environments such as those facilitated by IT (Overby and Konsynski 2010). In process virtualization theory, it is posited that certain process characteristics (sensory requirements, relationship requirements, synchronism requirements, and identification and control requirements), which represent the main constructs of the theory, and IT characteristics (representation, reach, and monitoring capability), which represent the moderating constructs of the theory, affect the dependent variable "process virtualizability", i.e., the amenability of a process to being conducted virtually (Overby 2008). Thus, the theory views it as a key premise that IT can be used to raise the amenability of a process to being virtualized by contributing to the satisfaction of sensory, relationship, synchronism, and identification and control requirements. As it was our goal to develop a method that guides us in explaining why we see a proliferation of tasks and processes being subject to cognitive automation, which has not been observable one decade ago, we specifically considered the role of AI Technology (AIT). We found the explanatory structure of process virtualization theory (Overby 2008) to be a very valuable orientation point for our research endeavor that we could build upon by using its underlying logic and phenomenon-oriented lens to guide our method development. Therefore, using Process Virtualization Theory helped us to determine the major design requirements the method needs to fulfill – i.e., the methods needs to consider the moderating effect of AIT in relation to the requirements that are induced into projects by the particular characteristics of cognitive automation use cases.

In order to tailor this structural logic to the specificities of cognitive automation, in *DSR phase 2*, we thus needed to identify the relevant dimensions along which a cognitive automation use case can be characterized in terms of the requirements its characteristics impose on a cognitive automation endeavor. This set of assessment dimensions should allow for generalizability and hold across various organizational contexts. As theoretical research in this vein was still nascent, we induced the dimensions from the organizational context. Thus, we seized the technique of semi-structured interviews (Longhurst 2003) with practitioners from the field. We purposefully selected the interviewees to achieve a high level of variation. To still maintain comparability between the interviews, the interviewees were selected from representatives of large corporations, who were involved in cognitive automation projects. Over the duration of one year (03/2019 - 03/2020), we interviewed 17 company representatives from various industries, who were involved in nine cognitive automation projects and were based on different hierarchy levels of the organizations. Table 1 provides an overview of the interviewees.

Based on the interview transcripts, two researchers extracted data from the material and engaged in open, axial, and selective coding (Forman and Damschroder 2007). After openly coding the documents and assigning relationships among the open codes (axial coding), we set the core variable for selective coding to be "requirements dimensions of use case characteristics" to identify factors that need to be assessed to determine the degree to which a use case is suitable to cognitive automation. We iteratively evaluated the coding in discussions among two researchers to reach validity and reproducibility (Forman and Damschroder 2007). This led to four assessment dimensions of the use case characteristics: cognition, data, relationship, and transparency requirements. Furthermore, we developed a structured set of questions that operationalize respective sub-constructs and items to grasp the four assessment dimensions. These were deduced from literature to enrich the induced practice-oriented dimensions with construct clarity from research (Suddaby 2010).

| **Project** | **Industry** | **Goal of Cognitive Automation** (i.e., Task(s) to be Automated) | **Positions of Interviewees** (Number of Interviews/Total Duration) |
|---|---|---|---|
| Alpha | Telecom-munication | Classification and Routing of Incoming Client Emails | Capability Management Head (1/30 min.) |
| | | | Project Owner from Business (1/60 min.) |
| | | | Project Manager (1/60 min.) |
| Beta | Banking | Translation of Financial Documents from Italian and French to German | Chief Information Officer (1/40 min.) |
| | | | Project Manager (2/120 min.) |
| Gamma | Manufactu-ring | Price Setting for Individualized Technical Offerings | Chief Information Officer (1/30 min.) |
| | | | Project Manager (2/80 min.) |
| Delta | Banking | Classification, Routing and Resolution of Internal Incident Tickets | Head of Data and Analytics (1/40 min.) |
| | | | Head of Platform Strategy (1/35 min.) |
| | | | Project Manager (2/120 min.) |
| Epsilon | Manufactu-ring | Classification, Routing and Resolution of Company-Internal Incident Tickets | Vice President IT Innovation (1/50 min.) |
| | | | Project Manager (1/50 min.) |
| Zeta | Automotive | Reception of Appointment Bookings | Executive Manager AI Strategy and Architecture (1/ 110 min.) |
| Eta | Manufactu-ring | Criticality Review of Supplier and Sales Contracts | Project Manager Business (1/45 min.) |
| | | | Project Manager Legal (1/45 min.) |
| Theta | Pharma | Determination of Cell Types | Senior Data Scientist (1/120 min.) |
| Iota | Insurance | Routing and Control of Claims | Chief Data Officer (1/120 min.) |
| **Overall Number of Interviewees / Interviews:** | | | **17 / 20** |

**Table 1. Interview Information**

Moreover, to take into account the moderating role of AIT, the distinguishable characteristics of AIT were deduced from literature. The specific characteristics that AIT exhibits are enabled by advancements in algorithms, computing power, and data storage (Jordan and Mitchell 2015; von Krogh 2018). In that, AIT can help to make a use case more amenable to cognitive automation, which means that AIT positively moderates the relations between the main constructs – cognition, data, relationship, and transparency requirements – and suitability of a use case for cognitive automation.

To conduct a first evaluation cycle of the identified assessment factors of the method (*DSR phase 3*) in terms of exhaustiveness, understandability, and potential utility for practice, we drew on a focus group (Longhurst 2003) consisting of four Chief Information Officers (CIOs), which underlined the relevance of developing a method for assessing cognitive automation use cases. Furthermore, it supported the general structure of the research model, i.e., taking into account use case characteristics and the moderating role of AIT.

Therefore, we continued the DSR journey and iteratively identified and structured method components (*DSR phases 4-6*), which helped to embed the cognitive automation-specific use case assessment factors in the method components. These method components were then complemented with tool support from existing research and tools that we developed ourselves to live up to the specificities of cognitive automation. This process was informed by multiple interviews with experts from various industries (see Figure 1) to facilitate constructing a method, which is industry-agnostic but adaptable to different contexts.

After presenting the finalized method artifact to two Machine Learning experts of a global provider of RPA automation solutions, who had the goal to move beyond RPA towards cognitive automation in their consulting and implementation practices, we could reach a PoC of the method. To reach a first summative evaluation of the method and to consider the specificities of applying it in the real-world organizational context, we applied the method ourselves in a 9-month action research project (*DSR phase 7*) with a leading manufacturing company from the sanitary industry. The company intended to assess the use case of deploying cognitive automation in their customer support department. Therefore, we set up an action research team (Baskerville 1999) consisting of two researchers that developed the assessment model and two project managers from the company – one from the IT and one from the business department. Subsequently, we embedded the use case assessment in the action taking phase, which is part of the five phases of the action research cycle (Baskerville 1999): *(1) diagnosing, (2) action planning, (3) action taking, (4) evaluation, (5) specifying learnings*. The project led to a positive evaluation of the method, and helped the Chief Information Office (CIO) and the Chief Marketing Officer (CMO) to reach a conclusion on how to proceed with the use case. The results could be used to inform business planning and getting buy-in from the CEO of the company, which positively speaks for the usability of the method and the value of its outcomes (PoV). This is reflected in the following two quotes by the CMO and the CIO of the action research company:

*"Now we are one round smarter again, but we also have a lot of luggage in our backpack. [...] These are important points that came out of the analysis."* – CMO of Action Research Company

*"I will bring the results to the next steering meeting for next year's [2021] business planning."* – CIO of Action Research Company

In *DSR phase 8*, we aimed at further evaluating the method along the two dimensions for evaluating IS methods proposed by Moody (2003): actual efficacy, i.e., whether the method improves task performance, and adoption in practice, i.e., whether the method is used in practice (Moody 2003). Therefore, the research team taught the method to two student teams from a leading European business school in two 2h-sessions. Then the students applied the method in two real-world projects. One student team applied the method in an organization from the digital retail industry, and the other team in the banking industry. The two projects lasted three months. Overall, these led to successful outcomes with regards to the method's actual efficacy and adoption in practice as the method facilitated two student teams to use the method for helping respective company representatives to gain decision-support regarding their cognitive automation use cases. In the digital retail industry, the students successfully helped an ML product owner to assess the use case of automated routing of defective devices to the particular service centers. In the banking industry, the other student team supported a business analyst in assessing the use case of automating data quality assessments of bank reports. On this basis, the research team was further facilitated to identify steps for improvement in terms of increasing the efficiency of organizational method embedding to transfer it to continued usage in organizations (*DSR phase 9*). Thus, the DSR journey towards a PoU continues by introducing the method in further organizations to enable them to assess cognitive automation use cases themselves at scale seizing IT tools (i.e., instantiated method artifacts) supporting the efficacy and efficiency of the assessment according to Moody (2003).

# Results

Figure 2 depicts the resulting method for assessing cognitive automation use cases.

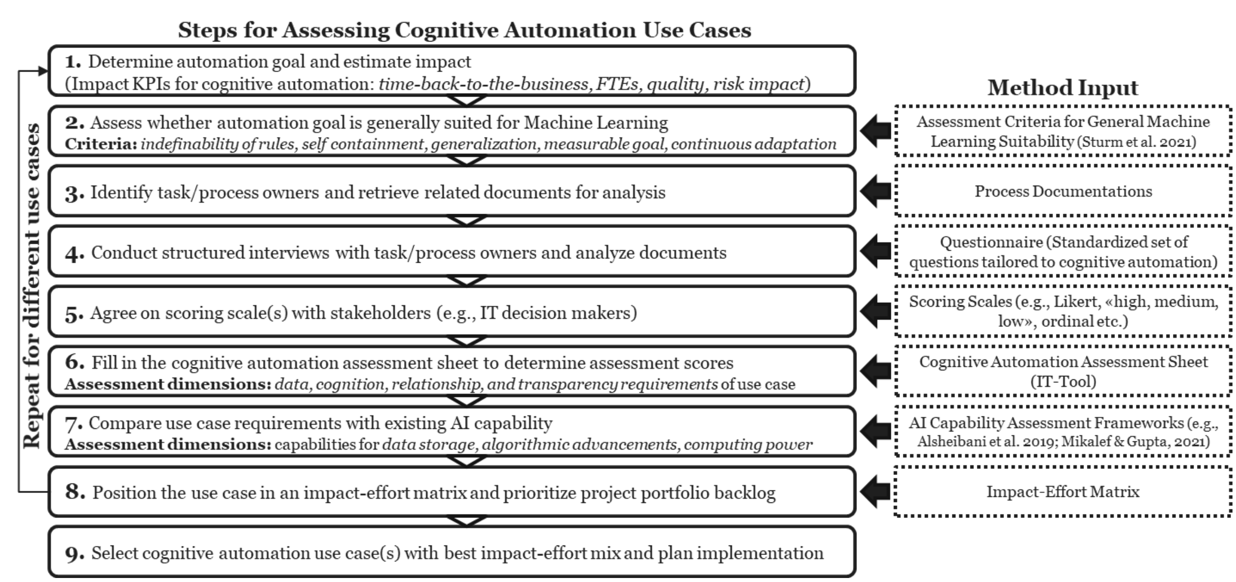


**Figure 2. Cognitive Automation Use Case Assessment Method**

The method consists of nine steps that reach from determining the automation goal and the expected impact (i.e., time-back-to-the-business, fulltime equivalent (FTE), quality, risk impact) and assessing general AI suitability of a task or process to assessing the specific dimensions of cognitive automation use cases in structured interviews with task and process owners along data, relationship, cognition, and transparency requirements. It further guides the user through comparing the use case requirements with the existing AI capability (i.e., organizational capabilities for utilizing the advancements in data storage, algorithms, and computing power). Finally, this results in the last steps of positioning and prioritizing the use case(s) in an impact-effort matrix, which facilitates decision-making on which use case to implement from the portfolio. We complement the method with a set of existing tools from research and practice (e.g., impact-effort matrix), and develop own tool support (e.g., standardized set of assessment questions, IT-based scoring model etc.) to tailor the method to the specifics of cognitive automation.

### *Step 1: Determine Automation Goal and Estimate Impact*

In the first step of the cognitive automation use case assessment method, the use case assessor needs to (re)define the business need of the use case. This is crucial to determine the concrete goal that the potential application of cognitive automation technologies shall achieve and to estimate the impact the use case can have on the organization. Therefore, cognitive automation use case assessors need to clearly define the key performance indicators (KPIs) in terms of return on investment (ROI) they aim to contribute to. There are four main groups of KPIs suitable for cognitive automation: *time-back-to-the-business*, *fulltime equivalents (FTEs)*, *quality*, and *risk*.

*Time-back-to-the-business* refers to the time that is freed up for employees so they can invest it in more value-adding tasks (Lacity and Willcocks 2021). For instance, if employees spend 20 percent less time on routing and replying to emails, as this task is taken over by a cognitive automation software robot, they can use this time to strengthen ties to customers and thus add more value to the organization.

*FTEs* refer to either reducing headcount in teams or keeping it stable while simultaneously handling the surplus in work that might be steadily increasing, such as rising number of customer requests in a service helpdesk department.

*Quality* improvements in the realm of cognitive automation relate to software robots conducting a certain task or process better than the human counterpart would. This is especially the case in analytical tasks such as scanning through large data sets where system-2 thinking is prevalent (Kahneman 2011). Furthermore, software robots never sleep, which can for example raise customer service levels as voice or chatbots are available 24/7, 365 days a year.

*Risk* impact surrounds the field of using cognitive automation systems for the purpose of reducing ambiguity that might be rooted in subjectivity, inconsistency or bias of human decision-making. For instance, if contracts or loan applications are automatically screened by a cognitive automation system, the system will attain to the rationale that it was developed for seizing the relevant data points to predict the most likely outcome, which helps to improve risk management practices.

Once, the automation goal is clarified and well defined, the expected impact on *time-back-to-the-business*, *fulltime equivalents (FTEs)*, *quality*, or *risk* measurements can be quantified.

### *Step 2: Assess General Machine Learning Suitability*

The second step of the method poses a stage gate as use case assessors need to assess the general suitability of the task or process for being conducted with Machine Learning, i.e., the underlying technology of cognitive automation and AI in general. We use the assessment criteria proposed by Sturm et al. (2021) as a method input in this step. These determine whether a use case has a general fit to being resolved by a Machine Learning system or if another technological solution should be used – e.g., RPA.

Therefore, use case assessors need to assess the following five criteria according to Sturm et al. (2021):

*Indefinability of Rules*: If humans can define a set of deterministic rules, which are sufficient for generating a solution to a problem, then an IS other than Machine Learning or manual task or process performance should be preferred (Sturm et al. 2021).

*Self Containment*: This refers to the nature of the problem that shall be tackled in the use case. Apart from data availability and quality, the problem solution needs to be capturable with statistics, otherwise the Machine Learning algorithm will not be able to create reasonable solutions from data (Sturm et al. 2021).

*Generalization*: This refers to organizations being able to detect patterns that can be integrated into more general problem-solution fits (Sturm et al. 2021). Otherwise, using Machine Learning is not advocated and a different or no technology should be used for automation.

*Measurable Goal*: Use cases for which organizations cannot reach agreements on the correctness and quality of potential outcomes are not suited for Machine Learning as these systems require clear goals and metrics for producing adequate solutions (Sturm et al. 2021).

*Continuous Adaptation*: Organizations must check upfront if they can guarantee for continuous monitoring, retraining, and adaption of the Machine Learning system over time as the solution is likely to decrease in usefulness over time if changes in context data are not accounted for (Sturm et al. 2021).

### *Step 3: Identify Task and Process Owners and Retrieve Documents for Analysis*

If the use case is deemed to be generally suitable for cognitive automation, the third step of the method revolves around identifying the relevant task or process owners as well as related documents for analysis. Cognitive automation focuses on existing tasks and processes. Therefore, process documentations of the as-is process offer guidance for planning the subsequent interviews with the people who carry out the task or process, which shall be automated. Identifying the right task and process owners is furthermore a crucial step of reaching organizational acceptance of the planned endeavor as relevant stakeholders can be early integrated into cognitive automation initiatives, which makes it human-centered and tailored to the needs of the organization. If not clearly defined yet, in this step, the organization needs to (re)assign task or process owners responsible for the particular task or process under investigation to seize remediation opportunities.

### *Step 4: Conduct Interviews and Analyze Documents*

In the fourth step of the use case assessment, structured interviews with the task or process owners are carried out using a standardized set of 50 questions as a method input, which operationalize the essential assessment dimensions of cognitive automation use cases: data, cognition, relationship, and transparency requirements. These dimensions resulted from phase 2 of the DSR project (see methodological section of this paper) and are tailored to the specificities of cognitive automation. Table 2 visualizes a subset of the 50 questions, which operationalize the constructs within the requirements assessment dimensions. These questions should be combined with a personalized introductory set of questions to contextualize the analysis and to consider the personal background of the interviewees. However, due to page limitations, we cannot include all questions in this document.

Additional documents that were gathered in the preceding step support the answering of the assessment questions and help to produce transparent and reproducible assessment results. The interviews should be recorded and transcribed to achieve a high level of transparency and to allow for a clear assessment of the distinct requirements dimensions of the use case.

| | |
|---|---|
| Datedness | (1) How recently and how often must the information that employees need to perform their tasks be updated? |
| | (2) Do employees work with information that fluctuates over time, e.g. market data, price data? |
| Accuracy | (3) What errors occur through wrong interpretation of data or information by employees needed to perform their tasks? |
| | (4) What are costs of these errors? |
| Interpretability | (5) What are the different formats of data and information do employees need to handle to perform their tasks - images, vs. videos, vs. text, vs. audio? |
| | (6) How often does it occur that employees encounter data or information that they do not understand and have to ask for clarification? |
| Amount of Data | (7) How many different data sources do employees need for performing their tasks? |
| | (8) How much of this data do employees need to perform their tasks? |
| (...) | (...) |

**Table 2. Subset of Standardized Questions Assessing the Data Requirements of a Use Case**

## Step 5: Agree on Scoring Scales with Stakeholders

In the fifth step, the use case assessor defines how the assessment results shall be presented, i.e., whether a quantitative scoring shall be the prevalent mode of communicating the results or a predominantly qualitative indication is desired. This step is particularly crucial as organizations widely differ in how such insights are communicated. Here, it needs to be clarified to which extent the results shall be quantified and on what scale, e.g., Likert scale, "high-medium-low", or an ordinal scale sorting requirements of use cases.

## Step 6: Analyze Data, Cognition, Relationship and Transparency Requirements

Afterwards, the interview transcripts and documents are used to fill in the assessment sheet (method input), which was developed by the research team for the purpose of the cognitive automation use case assessment method. This means that the insights are matched with the assessment dimensions to determine the amount of time and monetary effort a particular use case will impose on the organization.

For all assessment dimensions we developed the set of standard questions in a manner that they allow to assess the constructs that span the dimensions of data, cognition, relationship, and transparency requirements. However, due to space constraints, we cannot describe all constructs in detail here.

Figure 3 exemplarily visualizes how the developed tool produces quantitative use case requirements assessment results if it has been agreed to use this kind of quantitative results representation. It shows how the single constructs determine the overall assessment score of the single requirements dimensions.

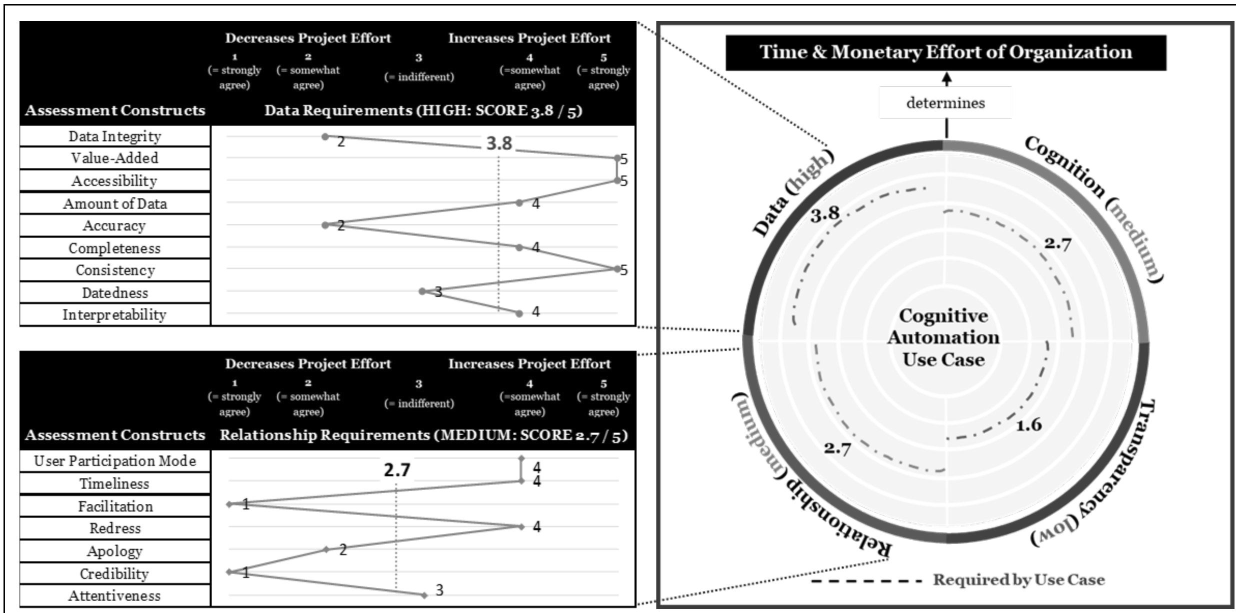


**Figure 3. Exemplary Requirements Representation Using Quantitative Scales**

*Data requirements* of a use case refer to the need for a cognitive automation solution to acquire, store and access data about the task or process input entities, the respective task or process outputs that shall be created, as well as the use case context. This induces challenges that are use case-specific and vary with the degree of data quality, which is widely defined as fitness for use (Cappiello et al. 2004). To assess the dimension of data requirements, use case assessors need to assess the constructs such as data integrity, accuracy, completeness etc. (Bovee et al. 2003; Cappiello et al. 2004; Pipino et al. 2002; Strong et al. 1997).

*Cognition requirements* of a use case refer to the needs that a task or process imposes on the capabilities of a cognitive automation tool with regards to entity perception, learning, reasoning, and interacting. Transferring tasks or processes from humans to machines implies the necessity of a machine to reconstruct the cognitive capabilities required to conduct the task or process (Rudowsky 2004). Thus, this dimension is linked to the construct of task complexity as a complex task has been defined as one, which imposes high cognitive requirements on a task agent (Campbell 1988). Therefore, use case assessors need to assess the constructs of size, variety, ambiguity of tasks etc. of the use case (Campbell 1988; Liu and Li 2012).

*Relationship requirements* of a use case pertain to the degree to which a cognitive automation tool needs to perceive and/or form social or professional bonds during task or process performance. In that, machines face several challenges in conveying social cues in the same manner as humans do (Louwerse et al. 2005), which is linked to research that focuses on how anthropomorphic features and behavior of machines affect the relation of a human towards machine agents (Rahwan et al. 2019). Here, use case assessors need to assess the required level of user participation (Barki and Hartwick 1994), and organizational response (Davidow 2003).

*Transparency requirements* of a use case are defined as the degree to which a cognitive automation tool needs to be capable of understanding and explaining what happens between task/process inputs and outputs. This assessment dimension relates to the research vein of “explainable AI”, which investigates the tradeoff between the accuracy of cognitive machines and their explainability (Bologna and Hayashi 2017). Use case assessors need to investigate constructs such as audit requirements (Bernstein 2017), and the distinct types of transparency such as in relation to stakeholders, meaningfulness etc. (Hosseini et al. 2016).

### *Step 7: Compare Use Case Requirements with existing AI Capabilities*

After the cognitive automation-specific requirements of the use case are determined, these are compared to the AI capability level that the organization exhibits to prepare the positioning of the use case in an impact-effort matrix in the next step.

This follows the reasoning that the AI capability level of an organization determines the time and monetary effort of implementing a use case with its particular requirements.

For these purposes, the AIT-specific capability dimensions for utilizing the advancements in data storage, algorithmic capabilities, and computing power need to be assessed or existing capability assessments can be used to inform this step. For these purposes, research has introduced new frameworks, which facilitate both a quantitative and qualitative assessment of organizational AI capabilities (e.g., Alsheibani et al. 2019; Jöhnk et al. 2021; Mikalef et al. 2019; Mikalef and Gupta 2021; Najdawi 2020; Yams et al. 2020). These can be used as method input to determine the AI capability of an organization in this step. Figure 4 visualizes how the AI capabilities can be qualitatively presented and communicated.

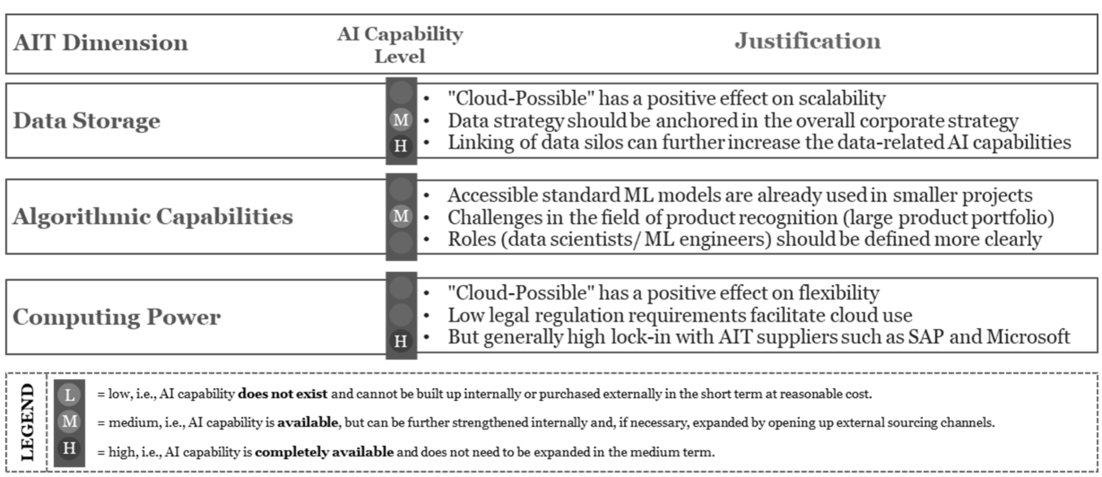


**Figure 4. Exemplary AI Capability Representation Using Qualitative Indications**

### *Step 8: Position Use Case in an Impact-Effort matrix*

Based on the requirements and capability assessment as well as the initial impact estimation (see step 1), the use case is then inserted into an impact-effort matrix to allow for prioritizing cognitive automation project portfolios. Respectively, the method steps 1-7 can be repeated for the set of tasks and processes that serve as candidates for cognitive automation and lead to a prioritized project portfolio backlog. Figure 5 showcases an exemplary impact-effort matrix, which serves as a basis for conducting the final method step.

### *Step 9: Select Use Case(s) with Best Impact-Effort Mix and Plan Implementation*

In the final step of the method, the impact-effort matrix is taken as the foundation for informing project (portfolio) planning. In this step the use case(s) with the best impact-effort mix are taken and structured on a project timeline. This allows to inform business planning of cognitive automation initiatives and to communicate accordingly for getting organizational buy-in such as project investments. Figure 5 visualizes an exemplary project plan of a cognitive automation initiative, which poses the final method output.

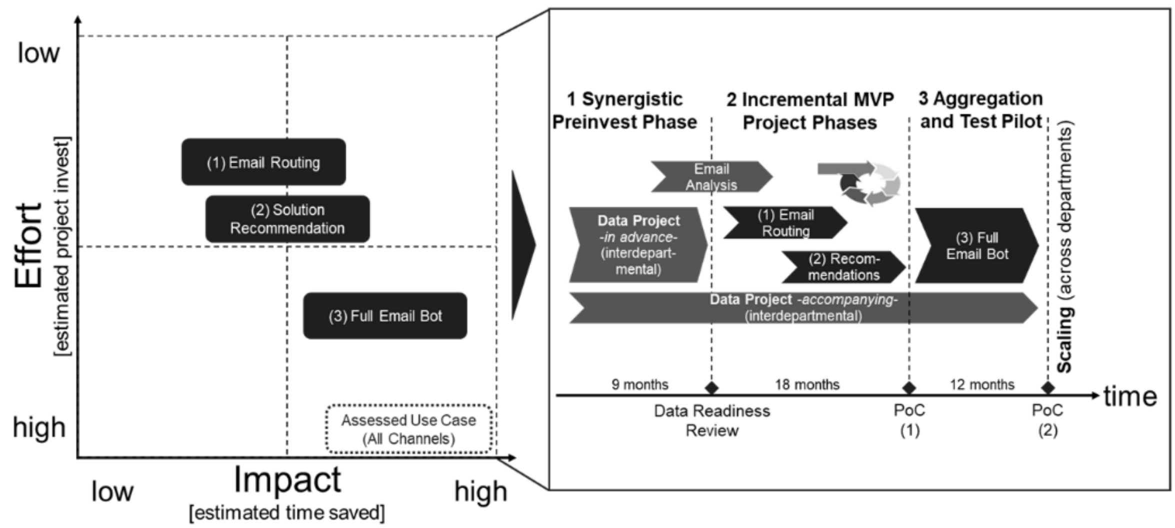


**Figure 5. Exemplary Impact-Effort Matrix and Project Planning**

## Discussion

Overall, our research pursued the goal to support IT leaders in assessing the suitability of cognitive automation use cases in a structured manner and to decide on whether and how to deploy them in their organizations. By developing the cognitive automation use case assessment model, we thus aim to make the following contributions to research and practice.

First, our method enables practitioners to make more informed decisions on selecting, specifying, and embedding cognitive automation use cases in their organizations and offers guidance on how to assess cognitive automation use cases. Furthermore, the method serves as a basis for developing diagnostic tools and services. For researchers, the method artifact shall serve as a structural and conceptual frame, which they can adapt or extend to both guide their empirical research or to use it as a foundation for developing future decision support for cognitive automation. This shall contribute to enriching the IS knowledge base on factors and steps affecting the adoption of cognitive automation, which deepens our understanding of the phenomenon of cognitive automation in particular, and AI in general.

Furthermore, in this paper, we build up on existing research from the realm of assessing AI and ML use cases (e.g., Hofmann et al. 2020; Sturm et al. 2021). Thus, we tailor our method for assessing cognitive automation use cases to the specificities of this novel phenomenon. We complement its methodical structure and set of assessment criteria with rich tool support and apply it in real-world contexts to showcase its PoV on an empirical basis. In that, we extend extant research by purposefully focusing on the phases following the exploration of general AI use cases. In cognitive automation, the divergent phases such as exploration and ideation of potential use cases are less emphasized than in cases with a broad general AI and ML scope, which also cover AI-based innovation or decision-support. This is because cognitive automation uses existing tasks and processes as a starting point for respective projects, which results in a smaller solution space. However, this does not mean that reengineering processes or tasks can be neglected in assessing cognitive automation use cases. In that, we intended to reach a level of abstraction in our method, which shall facilitate organizations to conduct in-depth assessments of existing tasks or processes.

Regarding a first summative evaluation of the method, we draw on the dimensions proposed by Moody (2003) in his method evaluation model, which has been developed to counteract the observation that in IS research, development of new methods is prevalent, while often the evaluation of methods is only addressed in a limited manner due to their normative character. Moody (2003) proposes two dimensions of evaluating IS methods: Actual efficacy, i.e., whether the method improves task performance, and adoption in practice, i.e., whether the method is used in practice. “On their own, neither actual efficacy nor adoption in practice will lead to improved practices” (Moody 2003, p. 4). We conclude that the original research team consisting of two researchers as well as two student teams from a leading European business school could use the method to enhance decision-making on cognitive automation use case implementation in real-world organizational settings (first indication for actual efficacy according to Moody (2003)), which supported business planning of three companies and triggered future projects on training the method to company representatives (first indication for adoption in practice according to Moody (2003)).

However, of course, this work is not free from limitations, which provides opportunities for future research. First of all, the summative evaluation of the method can be extended to more cases to strengthen the empirical basis for showing usability and robustness of the method artifact. This goes along with benchmarking the method in further research settings against comparable methods such as CRISP-DM or the methods, which we described in the related work section of this paper. Similarly, the method could be benchmarked against a setup of no method support, which requires collecting more empirical case data. Moreover, so far, the method does not optimize for achieving scalable use in organizations. This means that assessing multiple use cases against the backdrop of fast and efficient assessments in organizations has been out of scope so far. Here, we specifically advocate to dive deeper into the more detailed constructs of Moody's (2003) method evaluation model, and to investigate the latter in a more fine-grained manner – i.e., actual efficiency, actual effectiveness, perceived ease of use, perceived usefulness, intention to use, and ultimately actual usage of the method in organizations.

Therefore, we see the following opportunities for future research endeavors in this realm. Researchers can build up on the method by applying it in further case settings thus extending the summative evaluation of the method artifact. This offers the opportunity to derive method derivatives for different organizational contexts also including further remediation opportunities in the single steps of the method. In this vein, we also deem it necessary to further investigate the proposed model (step 6 of the method) in a more quantitative manner, e.g., by using the four requirements dimensions to craft use case prediction models, for instance by using logistic regression, structural equation modeling or cluster analysis. Furthermore, to approach the proof-of-use (PoU) of Nunamaker et al.'s (2015) last research mile, IT-based tool support (i.e., a technical instantiation of the developed method artifact) offers fruitful research avenues for future DSR projects on transferring the method to practice for continued use – i.e., taking into account efficiency metrics such as speed and costs of carrying out the assessment using our method. Ultimately, this can help to increase the scalability of the assessment of cognitive automation use cases in organizations such as developing employee-triggered self-service automation hubs for creating and handling use case backlogs.

## Concluding Remarks

This two-year DSR project pursued the goal to support current and future IT leaders in making more structured and informed decisions on whether and how to deploy cognitive automation use cases. Therefore, we developed a cognitive automation use case assessment method consisting of nine steps that allow for a more nuanced and in-depth assessment of cognitive automation project portfolios. This facilitates organizations to decide on respective initiatives and informs project portfolio planning. We applied the method ourselves in a 9-month action research project, which helped the CIO of the particular company to inform medium-term business planning, and equipped two business student teams with the method, which they applied in the online retail and banking industry. Overall, we can conclude that we could achieve our research goal of providing decision support to organizations when deciding on cognitive automation use cases. However, the DSR journey goes on to live up to the requirements of Nunamaker et al.'s (2015) last research mile for achieving a proof-of-use (PoU). Ultimately, this bears the potential to increase the success rates of cognitive automation initiatives in organizations and to deepen our understanding of the phenomena of cognitive automation in particular, and AI in general, to equip both researchers and practitioners for shaping the future of work.

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