

11-10-2025

How to Identify Promising AI Use Cases Under Real Business Conditions: Learnings from OTTO

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Recommended Citation

Sturm, Simon; Schmid, Simon; Endejan, Marcel; Kressin, Björn; Christophersen, Timo; and van Giffen, Benjamin, "How to Identify Promising AI Use Cases Under Real Business Conditions: Learnings from OTTO" (2025). *ITAIS 2025 Proceedings*. 18.

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How to Identify Promising AI Use Cases Under Real Business Conditions: Learnings from OTTO

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Abstract. Various methods have been proposed to identify promising AI use cases. However, it is not known if these methods work under real business conditions (e.g., limited time and personnel for method execution). We address this issue by taking an alternative approach to method development: Action Design Research at Germany’s leading e-commerce company “OTTO”. We co-designed our method with practitioners through iterative cycles of building, organizational intervention, and evaluation. Our method synergizes Design Thinking and Fit-Viability Theory to identify AI use cases that are relevant and realistic for the business. We make two contributions. First, we provide a method that accounts for resource constraints faced in business practice. Practitioners can use the method “as is” or adapt it for their purposes. Second, we abstract our learnings into four principles for identifying promising AI use cases under real business conditions: Human-Centered Technorealism, Co-Creative Pragmatism, Adaptive Standardization, and Innovative Continuity.

Keywords: AI Use Case Identification, Method, Action Design Research

1 Introduction

Identifying use cases where artificial intelligence (AI) creates business value is a key challenge for many organizations [1]. From a business perspective, AI enables organizations to delegate increasingly complex tasks to “a distinct form of autonomous and self-learning agency” [2]. This general-purpose technology [3] offers organizations numerous opportunities to create value for customers, partners, and employees. The same is true for competitors. AI is thus becoming a major competitive force in highly digital industries such as e-commerce, insurance, and financial services [4]. Although managing AI for business value has become imperative for these organizations, most of them still struggle to generate business value from AI initiatives and adopt AI technologies at scale [5]. Identifying AI use cases that are relevant and realistic for the business is a persistent issue.

Consequently, the identification of AI use cases has received considerable attention. On the one hand, the literature concludes that organizations can – and should – identify AI use cases like other innovation opportunities: focusing on understanding relevant business problems first, then ideating, evaluating, and implementing the best solutions [6, 7]. On the other hand, the literature suggests that it is particularly difficult to achieve this problem-solution fit for AI [8]. A key challenge is that many people expect AI to perform much better than it realistically can [9]. Therefore, various methods have been proposed to help organizations identify AI use cases systematically [e.g. 6, 7, 10].

The problem is that we know little about whether the proposed methods for AI use case identification work in business practice. If evaluated at all [10], the methods have only been subjected to expert interviews [7] or instantiated in research-controlled environments [6]. The limited evaluation of real-world utility is a consequence of the research approaches chosen by previous method designers. For example, Brunnbauer et al. [6] and Hofmann et al. [7] followed design science research approaches that (1.) treat method construction and evaluation as distinct research activities, and (2.) do not require evaluation through real-world intervention [11]. As a result, existing AI use case identification methods tend to prioritize “rigor at the cost of organizational relevance” [12]. We address this issue and ask: *How to identify promising AI use cases under real business conditions?*

To answer the research question, we adopt an alternative approach to method development: Action Design Research [ADR; 12] at Germany’s leading e-commerce company “OTTO”. Throughout its 75-year history, OTTO has adopted new technologies to transform its business time and again. The company started as an analogue mail order business. Today, OTTO operates Germany’s largest e-commerce platform with over twelve million active customers, 6,500 partner companies, and eighteen million products.

The ADR approach allowed us to develop our AI use case identification method together with OTTO practitioners through iterative cycles of method construction, organizational intervention, and evaluation [12]. We make two contributions. First, we contribute a method for identifying promising AI use cases that accounts for resource constraints. Which we trust other practitioners may find useful to apply “as is” or adapt for their purposes. Second, we abstract our learnings into four principles for AI use case identification under real business conditions: *Human-Centered Technorealism*, *Co-Creative Pragmatism*, *Adaptive Standardization*, and *Innovative Continuity*.

This paper is structured as follows. First, we present a working definition of AI and introduce the theoretical perspectives that informed the design of our method (Design Thinking and Fit-Viability Theory, Chapter 2). We then document the research process (Chapter 3) and specify the components of our AI use case identification method (Chapter 4). Next, we illustrate its application at OTTO (Chapter 5). Finally, we abstract the learnings from our joint research initiative (Chapter 6) and offer concluding remarks (Chapter 7).

2 Conceptual Background

2.1 Artificial Intelligence (AI)

The term “artificial intelligence” was coined in the mid-1950s [13]. There is no universal AI definition [14] because the intelligence concept itself is contested [15]. Broadly speaking, however, AI refers to the ambition of mechanizing human-like reasoning and behavior [13]. The recent surge in AI is primarily driven by advances in machine learning technology (ML) [16].

As the term ‘machine learning’ implies, ML is an approach to mechanize human-like reasoning and behavior in which computer systems are not explicitly programmed, but to learn from data [17]. This means that ML-based AI systems do not require human-coded rules to interpret information [17]. Instead, ML-based AI systems use computational representations (i.e., models) which they infer from training data using statistics [18]. Consequently, ML-based AI systems tend to operate with a higher degree of autonomy and be more inscrutable than other information technologies [19]. In this paper, we use the term “AI” to refer to machines and computer systems that incorporate ML components.

There are many ways to conceptualize ML-based AI. For example, by learning paradigm (i.e., supervised, unsupervised, reinforcement learning [18]). In this paper, we adopt a functional perspective and conceptualize ML-based AI by the types of problems ML-based AI is typically used to solve [9]. To this end, we build on the eight high-level AI capabilities proposed by Yildirim et al. [9]: *Estimate*, *Forecast*, *Compare*, *Detect*, *Identify*, *Discover*, *Generate*, and *Act* (see Table 1). This functional perspective backgrounds algorithmic mechanics and foregrounds the purpose(s) that ML-based AI systems serve in a business context (i.e., the task(s) that ML-based AI is used to augment or automate). The key benefit of this functional view is that it fosters close collaboration between business domain, IT, and data science experts [5]. After all, high-level capabilities (e.g., estimate) help translate business tasks (e.g., assessing a current state) into ML algorithms (e.g., linear regression) and vice versa. We designed our AI use case identification method to leverage this strength.

Table 1. Taxonomy of High-Level AI Capabilities. Adapted from Yildirim et al. [9].

AI Capability	Definition	AI Use Case Example
Estimate	Assess current state	Estimate likelihood email is spam
Forecast	Predict future state(s)/event(s)	Forecast best time to buy stock
Compare	Compare objects by metric	Compare posts by engagement likelihood
Detect	Notice presence of object type(s)	Detect human voice in audio
Identify	Notice presence of specific object(s)	Identify cancer type in medical image
Discover	Recognize (dis)similarities of objects	Discover unusual bank transactions
Generate	Create similar object(s)	Generate synthetic medical records
Act	Execute/optimize decision rule(s)	Act: Fly drone to location

2.2 Identifying AI Use Cases

Consistent with our functional understanding of ML-based AI, we assume that the value of an AI use case lies not in the technology per se, but in the business task that ML-based AI is used to support [20, 21]. Which implies that promising AI use cases meet two criteria: They are *relevant* (i.e., address a major business need) and *realistic* (i.e., technically feasible and implementable within constraints of the business). Many valuable AI use cases are not readily available [8]. However, businesses can identify them in structured processes [6]. As others have shown [6, 7, 10], the identification of promising AI use cases involves both *generation* (coming up with potential AI use cases) and *evaluation* (assessing the extent to which AI use cases are relevant and realistic for the business).

Our AI use case identification method draws from two complementary kernel theories [22]. Design Thinking informed the *generative*, and Fit-Viability Theory the *evaluative* method components. We did not select the kernel theories in advance. They emerged during the research process.

Generating AI Use Cases: Design Thinking (DT).

Design Thinking (DT) is a human-centered innovation approach [23]. DT provides a “mindset, process, and toolbox” [24] that helps non-designers innovate by adopting “a designer’s sensibility and methods to match people’s needs with what is technologically feasible and what a viable business strategy can convert into customer value and market opportunity” [25].

DT rejects the theory of lone innovative genius [26]. Instead, DT proposes that innovation occurs through “disciplined teamwork that follows a creative human-centered discovery process” [25]. The design and consulting firm IDEO provides a well-established DT process model [25]. IDEO’s [27] model breaks human-centered innovation into three phases that are progressed iteratively: *Inspiration* (discovering human needs worth innovating for), *Ideation* (generating, developing, and testing solution ideas), and *Implementation* (turning ideas into real-world solutions).

DT has proven to be an effective innovation catalyst in various business applications [23], including the development of digital products and services [28, 29]. AI offers new possibilities to innovate human experiences [30]. However, AI-driven innovation will not necessarily improve the way people interact with technology and another. It may even lead to unintended, harmful consequences. Microsoft’s chatbot Tay, for example, quickly turned into a racist hate machine [31]. Therefore, the design of human-centered AI systems has received much research attention [e.g., 32, 33]. DT is a promising way to develop human-centered AI innovations [34] for two key reasons. First, DT’s exploratory problem-solving approach provides the necessary flexibility to manage AI innovations, many of which are experimental by nature due to data dependency [20]. Second, by focusing on understanding human needs first, DT helps reduce uncertainty early and at low cost: Before resources are spent on building AI solutions (e.g., collecting and cleaning data, engineering features, building pipelines, training models, etc.) only to find out later that the AI solution is not wanted by users or not viable for the business, and therefore unlikely to add value.

Our method uses IDEO’s DT process model to organize the identification of AI use cases and ensure that *generative* activities (coming up with potential use cases) focus on *relevant* business needs. While DT recognizes the importance of evaluation [25], it provides little guidance on determining if an AI use case is *realistic* (i.e., technically feasible and implementable within constraints of the business). Therefore, we use Fit-Viability Theory as a second kernel theory.

Evaluating AI Use Cases: Fit-Viability Theory (FVT).

Fit-Viability Theory (FVT) explains the organizational adoption of technological innovation. FVT proposes that successful adoption depends on two aspects. First, the extent to which the technology meets the requirements of the business tasks that it is supposed to support (“fit”). Second, the degree to which the organization can integrate and sustain the technological innovation (“viability”). FVT also has a prescriptive element. It recommends that organizations map initiatives along the dimensions of fit and viability to decide which innovation opportunities to pursue (Figure 1). FVT was introduced to help organizations manage transformation initiatives during the early days of the Internet [35]. However, FVT constructs are not specific to Internet characteristics. FVT has therefore been applied to a wide range of digital technologies [36, 37], including AI [38, 39].

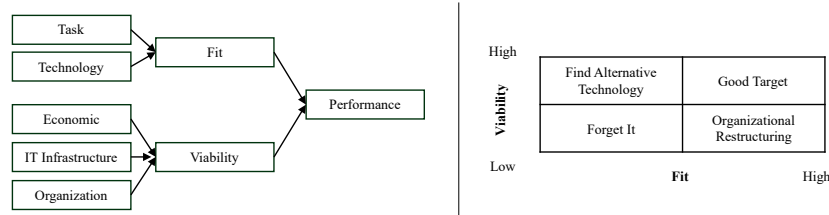


Figure 1. Fit-Viability Constructs and Fit-Viability Portfolio Matrix.
Adopted from Liang et al. [36] and Liang & Wei [40].

Our method uses FVT to evaluate AI use cases regarding (1.) the degree to which AI characteristics (autonomy, inscrutability, learning) [19] align with the business task that AI is supposed to support and (2.) the degree to which the business is likely able to develop and maintain an AI solution at the desired level of performance. *Fit* is considered high when AI is the only or preferred method for solving a business problem (e.g., complex optimizations where human intelligence and rule-based systems reach their limits). *Fit* is considered low when ML-based AI characteristics do not align with or contradict the logic of a business task (e.g., using inscrutable neural networks for hiring decisions, which are expected to be transparent and explainable). *Viability* is considered high when the necessary conditions are met for the business to develop/maintain AI at the expected level of performance (e.g., high-quality data is accessible, technical infrastructure and relevant expertise are present, etc.). *Viability* is considered low when significant hurdles exist (e.g., resource constraints, inflexible business processes, ethical concerns, or resistance to the AI solution). By qualitatively assessing and comparing

use cases along fit/viability dimensions, FVT helps our method identify promising AI use cases to feed into subsequent innovation management activities. The main advantage of using FVT is that it foregrounds the reflection on whether a business task can (and should) be supported by AI. This reflection is particularly important in early-stage AI innovation but backgrounded in alternative evaluation methods (e.g., impact-effort assessment) [41]. We detail the design process of our method in the next section.

3 Action Design Research Process

We undertook this research to develop a method for the systematic identification of AI use cases. To ensure real-world utility, we chose an ADR approach [12].

As mentioned in the introduction, ADR challenges the assumption in traditional design science research that building and evaluation are distinct activities that can be separated into different phases [11, 12]. Instead, ADR assumes that design is an iterative process in which building, intervention, and evaluation are inherently intertwined [12]. ADR views artifacts as ensembles shaped as much by the organizational context in which they are designed as by the researcher’s intent [12]. Consequently, ADR generates general design knowledge by abstracting learnings from solutions that have proven useful in specific organizational contexts [12]. ADR thus involves a deliberate trade-off: it is better to build specific solutions and ensure they work somewhere than to pursue general solutions without knowing if they work anywhere. Previous research has shown that this context sensitivity makes ADR particularly well-suited for developing solutions to complex, real-world challenges, such as identifying use cases for emerging technologies [e.g., 42, 43].

We conducted our ADR project and co-designed our AI use case identification method together with OTTO practitioners from January to September 2024. Following Sein et al. [12], we summarize our ADR process as follows.

In the *problem formulation* stage, we diagnosed scalability as the main problem with OTTO’s existing approaches to AI use case identification. This means that existing methods would have required excessive resources (i.e., time, personnel) to identify a larger number of AI use cases that are *relevant* and *realistic* for OTTO’s business. In this context, OTTO’s strategic program for the business value-oriented use of AI technologies (“PushingAI”) is a key stakeholder. Therefore, our ADR team included academics and PushingAI practitioners (i.e., OTTO’s Chief AI Officer, the PushingAI Program Manager, and a Project Manager). We studied how OTTO had previously identified AI use cases by conducting user interviews, several workshops, and analyzing company documentation. We traced the scalability issues to the ways in which existing methods matched business needs and (potential) AI solutions. We found that the methods tended to (1) focus more on teaching how AI algorithms work than on learning about the business task(s) they are supposed to support, and (2) put considerably more effort into evaluating AI use cases than into generating them. The AI innovation literature [e.g., 6, 8] led us to conclude that OTTO had tended to follow technology-driven approaches. We decided to explore alternatives.

In the *build-intervention-evaluation (BIE)* stage, we envisioned a human-centered approach to AI use case identification at OTTO. Our idea was that starting with the needs of customers, partners, and employees would make it easier to find promising AI use cases than working backward from the technology. On reviewing the literature, we found that several human-centered methods for AI use case identification have been proposed [e.g., 6, 10]. However, as problematized in the introduction, their real-world utility has yet to be proven. Therefore, it was unclear whether the proposed methods would outperform the approaches OTTO had tried before. The ADR team thus concluded that it was necessary to develop a new method.

We detailed our vision of human-centered AI use case identification iteratively. In the process, we discovered that DT and FVT had complementary strengths that our method could interweave (see section 2.3). Essentially, our idea was to channel the power of DT’s “sensibility and methods” (Brown, 2008) into what is critical for successful AI adoption. We achieved this by enriching IDEO’s [27] DT process model with FVT constructs [36]. The result was the basic structure of our AI use case identification method: A two-stage approach that cascades through adoption-critical dimensions (*Task, Technology, Fit, Viability, and Performance*) as it moves from *Inspiration* (discovering human needs worth innovating for) to *Ideation* (developing and testing AI-based solution ideas). We fleshed out the basic structure of our method in three BIE cycles. We used DT, FVT, and the learnings from interventions at OTTO to detail the method components.

Page limitations do not allow us to discuss every design decision made during our ADR process (Figure 2). However, we report the most important ones as follows.

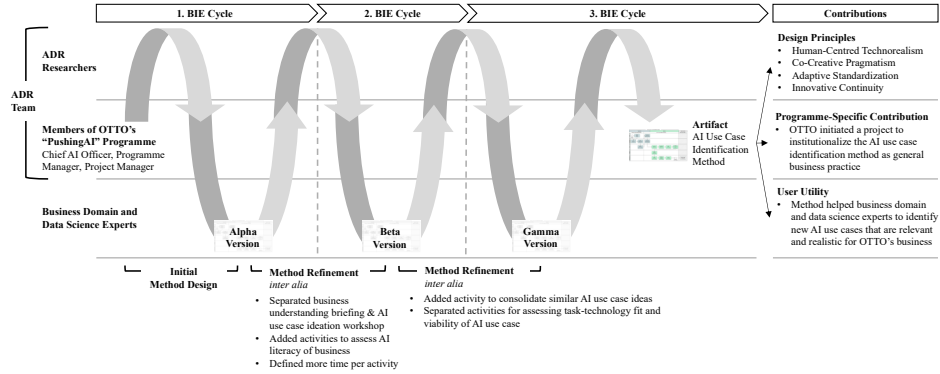


Figure 2. ADR Cycles and Contributions. Adapted from Sein et al. [12].

In the first BIE cycle, we prototyped an initial AI use case identification method (Alpha). Alpha detailed the activities, techniques, and tools for matching business needs with potential AI solutions. We designed Alpha to prevent mismatches caused by the common tendency to overestimate AI capabilities [8, 9]. Prior to ideation, educational activities ensure a shared understanding of what AI is, what kind of problems AI can solve, and how AI solves them. To this end, we explain the distinct features of contemporary AI technologies (i.e., autonomy, inscrutability, learning) [19] and their high-

level capabilities (i.e., estimate, forecast, compare, identify, detect, discover, generate, act) [9]. As explained in the conceptual background, these high-level capabilities offer a shared vocabulary for business and data science experts to discuss the use of AI in a business context, because they can translate business (e.g., detect fraud) in machine tasks (e.g., flag anomalous user behavior) and vice versa. Understanding the characteristics of AI (i.e., autonomy, inscrutability, learning) [19], on the other hand, helps business and data science experts reflect whether an AI solution fits the business task at hand and could realistically be implemented. The eight high-level AI capabilities [9] also guide the use case ideation. To this end, we analyzed how OTTO uses these capabilities (i.e., estimate, forecast, compare, identify, detect, discover, generate, act) [9] in the >65 AI use cases documented in a central repository. Based on this analysis, we created 44 AI use case pattern cards that help develop new AI use cases by analogy (e.g., by asking “*What if we could detect unusual behavior?*” and providing examples). Our idea was that (re)combining patterns from existing AI use cases would increase the likelihood of finding AI use cases that could also be implemented given OTTO-specific constraints (e.g., data, know-how, infrastructure). For they contain sensitive information, we cannot share these patterns in this paper. However, others can use open-source material [e.g., 44] to use our method or create custom ideation resources as well.

We evaluated Alpha by introducing it to two data science team leads. Both had identified many AI use cases at OTTO before and were potential end-users of our method. The experts liked Alpha’s human-centered approach and the techniques/tools for grounding ideation in technical reality. However, they noted AI literacy varies widely across business units in large organizations like OTTO. Therefore, our standardized method should also be adaptable to the application context. The experts also recommended to allocate more time to all activities to ensure they can be completed in business practice.

In the second BIE cycle, we incorporated the expert feedback and revised our method for greater adaptability. The Beta version split AI use case identification into *Business Understanding Briefing* and *AI Use Case Ideation Workshop*. The *Business Understanding Briefing* determines the business need(s) on which the *AI Use Case Ideation Workshop* will focus on. It also assesses the AI literacy of participating business domain experts and adapts the education components. For evaluation, we simulated an *AI Use Case Ideation Workshop* with five data scientists. All of them had recently applied one of OTTO’s technology-driven approaches to identify AI use cases. The data scientist stated that our method made it easier to find promising AI use cases. They also found Beta to be pragmatic (“not over-academic”) and thus likely to work in business practice. However, they suggested improvements which we implemented in the next BIE cycle.

In the third BIE cycle, we revised our method for greater practicality. The Gamma version (1) added an activity to consolidate similar AI use case ideas, and (2) separated the evaluation of task-technology fit and viability to reduce cognitive load. For evaluation, we used Gamma to identify AI use cases in OTTO’s “Brand & Advertising” department (see section 5). We involved data scientists and data science team leads from previous ADR cycles. The human-centered approach helped business domain and data science experts to identify many AI use cases that were considered both *relevant* and *realistic*. Participants found the method effective and fun to apply. The data science

team leads wanted to make it a standard practice. The ADR team therefore agreed that Gamma met the intended purposes and concluded the method design process.

In the final *formalization of learning* stage, we reflected on our research initiative. Following Sein et al. [12], we discussed how initial assumptions had been challenged in the method design process. This resulted in a set of principles for the identification of promising AI use cases under real business conditions (Chapter 6). In the next section, we detail our method as one possible instance.

4 OTTO Method for Identifying Promising AI Use Cases

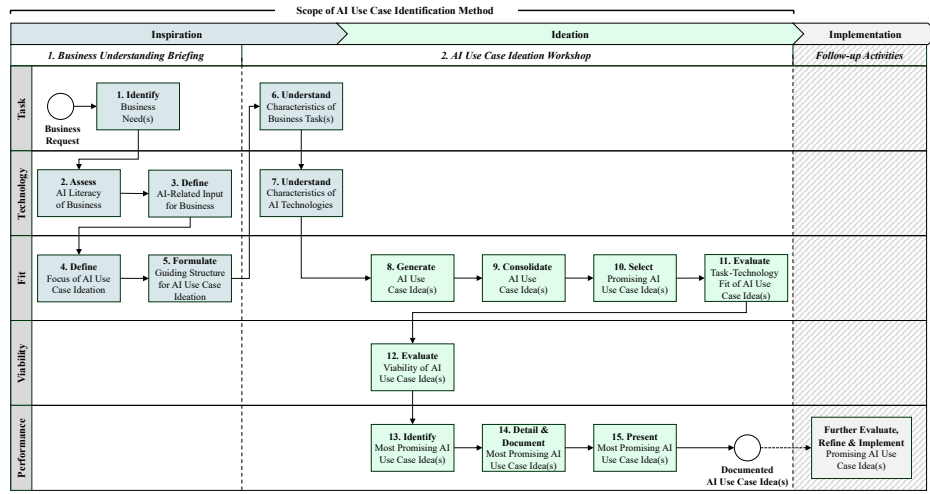


Figure 3. Process Model of Our AI Use Case Identification Method.

We suggest a two-phase approach to identify promising AI use case. Our method uses 15 activities [A] to move from *Inspiration* (discovering human needs worth innovating for) to *Ideation* (generating and evaluating AI-based solution ideas). As explained in the previous section, we designed the activity sequence to channel DT’s “sensibility and methods” (Brown, 2008) into what is critical for successful AI adoption. To this end, we enriched IDEO’s DT process model [27] with FVT constructs [36]. Figure 3 depicts the suggested activity sequence as a swim lane diagram. The x-axis shows to which AI use case identification phase an activity belongs (i.e., *Inspiration* and *Ideation*). The y-axis indicates which adoption-critical aspect it addresses (i.e., *Task*, *Technology*, *Fit*, *Viability*, or *Performance*).

Overall, the activities are structured into a *Business Understanding Briefing* and an *AI Use Case Ideation Workshop* (Figure 3). Our method returns a set of documented AI use case ideas for which there is good reason to assume that they are *relevant* and *realistic* for the business. These use cases are then fed into subsequent AI innovation management activities (*Implementation* phase), where they are further evaluated, refined, and ultimately implemented if they prove to be relevant and realistic for the business. Table 1 lists all the components of our method. It includes the recommended

techniques, tools, roles, and duration for carrying out the suggested activity sequence. We will discuss the activities and their function in more detail below.

Table 1. Components of Our AI Use Case Identification Method.

Activity	Technique	Tool(s)	Output	Role(s)	Dur.
<i>Business Understanding Briefing</i>					
1: Identify Business Need(s)	Identify relevant business challenges/ opportunities	 Reflection Questions	List of relevant business challenges / opportunities	— // —	45'
2: Assess AI Literacy of Business	Assess AI literacy of business unit	 Questionnaire	Understanding of businesses' AI knowledge / experience	— // —	15'
3: Define AI-Related Input for Business	Gather and specify AI-related input needs for the workshop	 AI-Input Wishlist	List of AI-related topics for introduction in the workshop	— // —	5'
4: Define Focus of AI Use Case Identification	Prioritize and select key business opportunities for AI exploration	 Group Discussion	Set of business challenge(s) / opportunities for AI exploration	— // —	15'
5: Formulate Guiding Structure for AI Use Case Identification	Reframe business challenge(s) / opportunities to guide subsequent AI use case identification activities	 “How Might We” Question, Design Challenge	Design challenge(s) guiding subsequent AI use case identification activities	— // —	45'
<i>AI Use Case Ideation Workshop</i>				SBE, BE; DSE, M	240'
6: Understand Characteristics of Business Task(s)	Explain business tasks, challenges, and needs in detail	 Design Challenge, Business Task Presentation	Shared understanding of business tasks, challenges & innovation opportunities	SBE	45'
7: Understand Characteristics of AI Technologies	Explain AI capabilities and real-world use cases	 AI Characteristics, AI Capability Taxonomy, AI Use Case Examples, (+ AI Input Wishlist)	Shared understanding of AI capabilities and realistic AI applications in business context	M	20'
8: Generate Realistic AI Use Case Idea(s)	Employ suitable creative tools to generate realistic AI use case idea(s)	 AI Use Case Pattern Cards (Assisted Brainwriting)	Initial pool of realistic AI use case ideas	SBE, BE, DSE	60'
9: Consolidate AI Use Case Idea(s)	De-duplicate, consolidate, and group AI use case idea(s)	 Clustering	Reduced pool of AI use case ideas	— // —	10'
10: Select Promising AI Use Case(s)	Select promising use cases idea(s) through group voting	 Dotmocracy	Set of promising AI use cases	— // —	5'
11: Evaluate Task-Technology Fit	Evaluate promising AI use case(s) regarding task-technology fit	 Fit-Viability Matrix	Differentiation of AI use cases by task-technology fit	— // —	15'
12: Evaluate Viability	Evaluate promising AI use case(s) regarding viability	 Fit-Viability Matrix	Differentiation of AI use cases by viability	— // —	15'
13: Identify Valuable AI Use Case(s)	Identify promising AI use case(s) by comparison	 Fit-Viability Matrix	Set of promising AI use case(s)	— // —	5'
14: Detail & Document Valuable AI Use Case(s)	Detail & document promising AI use case(s) in standardized format	 AI Use Case Canvas	Standardized documentation of promising AI use case(s)	— // —	40'
15: Present Valuable AI Use Case(s)	Present promising AI use case(s) for peer review & feedback	 AI Use Case Canvas, Elevator Pitch	Shared understanding of / feedback on promising AI use case(s)	— // —	25'

Legend: Inspiration Activity, Ideation Activity, — // — = The above is repeated;

Dur. = Duration, SBE = Senior Business Domain Expert, M = Moderator, BE = Business Domain Expert, DSE = Data Science Expert

The *Business Understanding Briefing* sets the thematic focus of the AI Use Case Ideation Workshop and adapts educational activities to the AI literacy of the business unit.

We therefore recommend conducting the Business Understanding Briefing with business unit leadership. The Business Understanding Briefing takes about two hours to complete and can be conducted online.

First, participants identify innovation opportunities [A1] by answering reflection questions (e.g., Which internal/external factors have a positive/negative impact on the success of our department?). The participants then use a questionnaire to assess the business unit's AI literacy [A2] and define what AI-related input will be provided in the ideation workshop ("AI Input Wishlist") [A3]. Finally, they decide which innovation opportunities to focus on [A4] and frame them as engaging design challenges ("How might we ...?") [A5] that will guide subsequent activities.

The **AI Use Case Ideation Workshop** generates and evaluates ideas on how AI technologies could solve the business need(s) identified in the Business Understanding Briefing. This requires both an understanding of business task(s) and AI capabilities. We therefore recommend one data science expert for every three business domain experts attending the workshop. The ideation workshop takes about four hours to complete. It can be conducted online, but we recommend face-to-face interaction whenever possible.

First, participants establish a shared understanding of the business need(s) that the ideation workshop will address [A6]. To this end, business unit leadership explains the business task(s) and introduces the design challenge. Participants thereby develop a shared understanding of business task(s) characteristics (e.g., error-tolerance, required accuracy, speed, transparency, etc.). They also learn about the technologies that are currently used to support these tasks, problems that remain unsolved, and the level of performance an AI solution would need to achieve to add value. Next, moderator(s) provide AI-related input tailored to the AI literacy of the workshop participants to ensure that everyone has the same understanding of what AI is and what kind of problems the technologies can realistically solve. To this end, we recommend explaining the characteristics (i.e., autonomy, instability, learning) [19], introduce the eight high-level capabilities of ML-based AI technologies (i.e., estimate, forecast, compare, identify, detect, discover, generate, act) [9], and to give examples where the business may already use them. The workshop then transitions from *Inspiration* to *Ideation*. The participants are divided into teams of 3-5. They use creative techniques to generate as many ideas how AI could be used to support the business task(s) as possible [A8]. As mentioned in the previous section, we found brainwriting assisted by AI use case patterns to be particularly effective in generating many potential AI use cases in a short period of time. Next, the teams cluster and consolidate their ideas [A9] and the workshop transitions to *evaluation*. The teams determine promising AI use cases through group voting ("Dot-mocracy") [A10]. Next, the teams evaluate each use case regarding fit between AI and business task characteristics [A11]. As explained above in more detail (see section 2.2), fit is considered high if AI is the only or preferred way to address the business task at hand (e.g., complex optimizations). Fit is considered low if AI characteristics do not align or contradict the logic of the business task. The teams then evaluate the viability of each AI use case [A12]. Viability is considered high if the business is likely able to develop and maintain the AI solution at an adequate level of performance. Viability is considered low if major hurdles exist (e.g., lack of data, necessary infrastructure, or

technical expertise). The teams then use the evaluation results to plot their AI use cases on a fit-viability matrix and identify their most promising AI use case [A13]. Finally, the teams detail their most promising AI use case in a standardized format (“AI Use Case Canvas”) [A14]. The goal is not to answer all questions right away, but rather to formalize how the use of AI could create value in a way that is easy to communicate, further evaluate, and refine in the future. To this end, the AI use case canvas helps the teams answer key questions (e.g.: *Who is/are the user(s)? What problem(s) does the use of AI solve for them? How does solving them benefit the business and align with business strategy? What are potential risks or unintended consequences of using AI? ...*). Finally, the teams pitch their most promising AI use case to all workshop participants for feedback [A15].

Our method hence returns a set of promising AI use cases, which are passed into subsequent AI innovation management activities, where they are further evaluated, refined, and implemented if they prove to be relevant and realistic for the business. The next section provides an application example.

5 Application Example: OTTO Brand Development

We used our method to identify promising AI use cases in a subunit of OTTO’s “Brand & Advertising” department (“Brand Development”). Brand Development ensures that advertisement is consistent and adheres to OTTO brand standards.

In the ***Business Understanding Briefing***, Brand Development leadership reflected on the key business challenges and opportunities. We then assessed the AI literacy of the business experts who would participate in the AI Use Case Ideation Workshop. To this end, we asked Brand Development leadership if their team had previously been involved in AI development and which, if any, AI training they had received. AI literacy was rather low. Leadership therefore suggested a working definition of AI and use case examples as pre-ideation input. Finally, we discussed which of Brand Development’s business need(s) to focus on and formulated two design challenges. Including: *How might we realize creative concepts for OTTO brand assets more efficiently?*

Three weeks later, we held the ***AI Use Case Ideation Workshop***. Ten business domain and three data science experts participated in person. First, Brand Development leadership introduced the two design challenges. They explained the business task(s), problems, and innovation opportunities in more detail. For example, they explained that the current briefing process between OTTO and creative agencies requires a lot of back-and-forth communication, which is resource-intensive and error-prone. Next, the workshop facilitators (OTTO’s PushingAI team) introduced AI fundamentals to ensure that all participants had a realistic understanding of AI’s possibilities and limitations in business applications (i.e., working definition of AI, AI’s high-level capabilities, and examples of AI use cases at OTTO). We then divided the business domain and data science experts into four mixed groups (3–4 members). Each team was assigned to one of the design challenges. The teams then conducted six rounds of assisted brainwriting. In each round, the participants randomly selected one of our AI use case pattern cards and jotted down as many AI use case ideas on sticky notes as possible. The four teams

generated 149 AI use case ideas, out of which 46 were considered promising through group voting (Figure 4).



Figure 4. AI Use Case Ideation Workshop Facts and Figures.

The teams then evaluated these 46 AI use case ideas based on task-technology fit/viability and mapped them onto a fit-viability matrix. The four teams then each selected their most promising AI use case, detailed it on an AI Use Case Canvas, and presented it to the other teams for feedback. The ideas included automated generation of briefing documents for creative agencies and the use of generative AI in digital content production. The participants agreed that these AI use cases were relevant to business challenges in the Brand Development department. With further evaluation pending, the participating data scientists considered the use cases realistic. Finally, we discussed how the identified AI use cases could be further evaluated, refined, and eventually implemented.

Both the outcomes (Figure 4) and the participant feedback indicate that our method is useful for identifying promising AI use cases under the resource constraints of business practice. As OTTO Brand Development leadership stated: *“The comprehensive and tailored input was an excellent introduction to AI for the whole team. [...] We generated many ideas for AI use cases that we want to concretize [...] and, of course, put into practice. The detailed pre-workshop discussions contributed significantly to the success [...]. The high level of practical relevance, the open exchange and ideation of potential AI use cases were not only appealing, but also a lot of fun!”*. We also collected feedback from workshop participants through a survey. We asked what they liked about the workshop and how it could be improved. The participants provided their responses in open-ended text fields. Following Gioia et al. [45], we analyzed the qualitative data by first open-coding the responses and then grouping the codes into aggregate dimensions. The participants’ statements indicate that they appreciated both the overall approach (*“The entire structure of the workshop was very positive”, “Workshop methodology”*) and the specific activities related to AI use case identification (*“The cards with examples of AI use cases”, “Introduction to AI”, “Workshop method”, “Working groups formed (different perspectives) = Opened minds, encouraged ‘free’ thinking”*). They also highlighted the importance of moderation and support during AI use case ideation (*“Organization, time management”, “Moderation”, “Everything was perfectly prepared!”*).

At the same time, participants suggested improvements, which we have incorporated. For example, they suggested more clarity on the next steps for refining and evaluating the AI use cases (“Specify the next steps in more detail at the end”), and to scope design challenge when introduced (“Where do we draw the line? What is not included in the ideation scope – e.g. video production, radio spots?”).

Our method has since been used in other departments (e.g., Quality and Product Compliance Management, and Advertising Services) and helped OTTO to identify many promising AI use cases across its business. We so trust that other practitioners may find our method useful and be interested in applying it “as is”. However, we developed our method using an action design research approach and recognize that it is not independent of the organizational context in which we designed it [12]. Therefore, we reflect on key method components below and abstract general recommendations for AI use case identification in business practice.

6 Principles for AI Use Case Identification Under Real Business Conditions

Table 2. Principles for AI Use Case Identification under Real Business Conditions.

Observed Challenge(s)	OTTO Solution Approach	Instantiation in OTTO Method (Exemplary)	Underlying Principle	Aggregated Principles
AI use case ideas do not address relevant problems	Focus AI use case identification on human needs (customers, partners, employees)	• Reflection questions • Design challenge • Business task presentation	Human-Centered Design	Human-Centered Technorealism
Ideas do not match what the business can realistically use AI for	Ground ideation in common understanding of AI use cases that the business can realistically develop & maintain	• AI-related input, ◦ AI characteristics ◦ High-level AI capabilities • AI use case patterns • Fit/viability evaluation	Technorealism	
Evaluating if AI use case is relevant / realistic requires different expertise	Foster collaboration between business and data experts	• High-level AI capabilities as shared vocabulary • Ideation & evaluation of AI use cases in interdisciplinary teams	Co-Creation	Co-Creative Pragmatism
AI use case identification is too complex or time-consuming	Use simple tools and formats that keep collaboration focused, lightweight, and time-efficient	• “Dotmocracy” voting • Fit/viability matrix • AI use case canvas	Pragmatism	
Different approaches are used to identify AI use cases across the business	Use the same activities, techniques, and tools to identify AI use cases	• Standardized approach to AI use case identification • Curated techniques & tools (e.g., AI use case pattern cards)	Standardization	Adaptive Standardization
AI use case identification does not align with situation at hand	Design the method to be adaptable to different business needs and levels of AI maturity	• AI-related input adapts to AI-literacy of business unit • AI use case ideation focuses on business design challenge	Adaptation	
Promising AI use cases are not picked up after ideation	Document AI use cases in a way that encourages further refinement, evaluation, and implementation	• AI use case canvas	Innovative Continuity	Innovative Continuity

Under real-world conditions, AI use case identification competes with other business activities for limited resources (e.g., time, personnel). AI use case identification methods must therefore be effective and efficient to have practical utility. Our ADR project started by imagining how this could be achieved in theory. We then developed our own

method and learned what it takes in practice. In this process, we observed challenges that likely arise when identifying AI use cases in business practice.

Following Sein et al. [12], we reflected on our learnings and abstracted them into four principles for identifying AI use cases under real-world conditions: *Human-Centered Technorealism*, *Co-Creative Pragmatism*, *Adaptive Standardization*, and *Innovative Continuity* (see Table 2). These principles encapsulate the fundamental concepts upon which the OTTO method is built. Unlike specific components, however, these principles are independent of the context in which we designed the method.

Therefore, we trust that other method designers will find these principles useful for adapting the OTTO method to their purposes or designing new AI use case identification methods for real-world use. To this end, we list the principles and offer corresponding recommendations below. **(1) Human-Centered Technorealism:** AI use cases should be identified by understanding what customers, partners, and employees need before searching for AI solutions that the business could realistically implement and sustain.

(2) Co-Creative Pragmatism: AI use cases should be identified through creative collaboration between business domain and data science experts. However, these interactions should not be over-organized, but given time, space, and simple tools to unfold.

(3) Adaptive Standardization: Standard activities should be defined to identify AI use cases in the business. However, they should be responsive to the context in which they are executed.

(4) Innovative Continuity: Use case identification should align with and feed into subsequent AI innovation management processes.

7 Discussion & Conclusion

We have conducted this research to address the issue of organizational relevance in the existing literature on AI use case identification. Unlike previous research, we have developed our method together with practitioners in three iterative cycles of building, organizational intervention, and evaluation. Our method synergizes Design Thinking and Fit-Viability Theory to identify AI use cases that are relevant and realistic for the business. It accounts for resource constraints and has proven effective in business practice. We thus propose design knowledge as an artifact (method) and a set of corresponding principles for identifying promising AI use cases under real business conditions. Which we argue contributes to theory and is useful for practice.

We contribute to the body of knowledge on AI use case identification [6, 7, 10] in two key ways. First, we challenge the implicit assumption of unidirectionality between the generation and evaluation of AI use cases in the existing literature. Previous method designers considered evaluation to take place after (potential) AI use cases have been generated, to filter out what is not promising for the business [6, 10]. This ex-post evaluation requires knowledge (i.e., criteria) about what makes an AI use case promising. We argue that additional value can be created if this knowledge is used not only to assess (potential) AI use cases, but also to guide the creative processes in which they are generated. Our method embodies this integrative approach to AI use case

identification which we position as an extension of existing work. Second, we add empirical insights to the literature. Unlike previous research [6, 7, 10], we built and evaluated our method together with practitioners under real-world conditions. We learned that organizational relevance is closely linked to the utilization of limited resources: the fewer resources a method requires to identify a greater number of promising AI use cases, the more useful it is for business practice. Our research implies that effectiveness and efficiency should thus be considered when designing for real-world use. We therefore propose our abstracted learnings as a starting point for future design research.

We also provide our AI use case identification method as an actionable resource for practitioners. Our method has proven its real-world utility by identifying promising AI use cases at OTTO. Other organizations may therefore be interested in using it “as is” or adapt for their purposes. To this end, we have articulated the “OTTO method” as a process model and detailed its components (activities, techniques, roles, output).

However, we acknowledge that our research has limitations. First, we chose an ADR approach. Therefore, we accept that our method is somewhat specific to the organizational context in which it was designed. OTTO is a highly AI-mature company with substantial in-house development capabilities. Other organizations within the same industry (e-commerce) or adjacent disciplines may not have the same resources or level of AI maturity. Consequently, they may require more, fewer, or other activities, techniques, and tools to identify promising AI use cases. Accordingly, we designed our method to be adaptable, so it can be revised and tailored beyond its initial context. For example, other organizations could use techniques other than assisted brainwriting to generate AI use case ideas. Second, our method's evaluation was formative and time bound. We relied primarily on workshop outputs and short-term feedback rather than long-term business impact measures. Thus, we cannot comment on our method's downstream performance (e.g., effects on AI adoption, ROI, or development cycle time).

These limitations present opportunities for future research. First, future studies could replicate and adapt our method across organizations with different levels of AI maturity in various industries and under different regulatory environments. Second, the method could be benchmarked against alternative approaches using common outcome metrics (e.g., time to proof of concept, proportion of ideas progressing to deployment, and realized business value). Third, future research could develop artifacts to support practitioners in executing the activities outlined in this paper (e.g., tools to document or evaluate AI use cases).

In conclusion, we hope our research will help others succeed in a world where AI is a rising competitive force. The winners will not necessarily be those who build the best AI models, but certainly those who know what (not) to use them for.

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