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GenAI-CoP: A Reusable Co-Creation Process for Identifying Generative AI Agents

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Abstract. Generative AI (GenAI) can enhance organizational processes and productivity. To realize these benefits, organizations must design GenAI agents that augment human work. A key challenge lies in making sense of the diverse forms of GenAI agents and aligning them with existing work processes. To address this, we propose a reusable co-creation process for identifying GenAI agents (GenAI-CoP) that enables organizations to involve domain experts in leveraging GenAI's potential for their products and workflows. Grounded in action design research (ADR), our approach draws on collaboration engineering to develop GenAI-CoP. We iteratively refined and tested it through simulations, expert interviews, and pilot tests. Our research contributes to GenAI and collaboration engineering literature by introducing a reusable, bottom-up identification procedure for GenAI agents. GenAI-CoP packages facilitation expertise, allowing practitioners to execute it without prior training in tools or techniques. They gain actionable guidelines to identify augmentation potential and summarize it as GenAI agents.

Keywords: Generative AI, Agents, Collaboration Engineering

1 Introduction

Interest in generative AI (GenAI) has grown significantly since the launch of ChatGPT in November 2022 [37]. GenAI represents a new class of advanced deep-learning models designed to perform a wide range of tasks and solve complex problems across multiple modalities. [2, 7]. Importantly, the rise of GenAI agents introduces a heightened level of agency [20], enabling them to access data, conduct complex reasoning, and seamlessly leverage existing tools and functions [8].

However, researchers highlight that in particular small and medium-sized enterprises (SMEs) have problems when confronted with radical types of innovation, such as

GenAI [16]. It is important to note that this is not merely the use of a technical tool; rather, it involves a fundamental change to work processes and a reallocation of work. This situation explains why today – according to a study by Gartner - only 29% of surveyed enterprises have deployed and utilized GenAI [12], while 83% believe that GenAI investments will increase over the next three years [1]. This demands structured approaches for identifying potential use cases for GenAI.

SMEs are challenged with identifying, assessing, and selecting GenAI agents within their organizational structures. In this realm, recent research on identifying suitable applications of GenAI has been driven by developing and assessing use cases and by considering rule-based and ML-based automation [6]. However, due to the novel class of GenAI technologies being deployed, traditional assumptions and approaches such as focusing on the technical capabilities [9, 12] do not hold anymore. We posit that a socio-technical focus is essential to enable employees who are domain experts to perceive and interact with GenAI agents as co-workers. Against the backdrop of the evolving nature of GenAI technologies, we highlight the lack of reusable procedural support for co-creatively identifying GenAI agents in collaborative settings. Accordingly, we propose the following research question: *How does a co-creation process have to be designed to facilitate the exploration of GenAI agents in business processes?*

We adopt an action design research (ADR) approach [31], involving a small- and medium-sized enterprise (SME) that aims to innovate their work processes and products with GenAI agents. Overall, we perform two iterative design cycles of formulating the design problem, building and evaluating the artifact, reflecting our learning, and finally formalizing our learnings as the resulting artifact. We formalize our aggregated design knowledge by contributing a *reusable co-creation process for identifying GenAI agents* (*GenAI-CoP*).

2 Related Work

GenAI changes how humans and AI work together to perform tasks [5]. GenAI leverages patterns from its extensive training data to generate new and unique outputs. It demonstrates human-like proficiency in processing and creating text, images, videos, and audio [7, 30]. Thus, GenAI, and particularly large language models (LLMs), show great potential for businesses [24]. Prior literature discussed its benefits in domains such as innovation management [3], customer service [32], and many more. Given the variety of tasks that GenAI systems can perform, it has been recognized as a general-purpose technology. Knowledge workers utilizing these systems, largely decide how and to which degree they utilize GenAI and delegate to GenAI agents [5]. Enterprises are encouraged to leverage these systems for competitive advantage by deeply understanding the technologies and identifying tailored enterprise-specific applications [23].

In research, scholars rely on reviewing existing literature to identify and systematize AI applications in various domains [19] or on exploratory methods such as semi-structured interviews [23]. However, this approach does not apply to practitioners as they are often confronted with very domain-specific conditions and challenges. Hence, prior studies on developing AI use cases emphasized the identification of problem-solution pairs [10, 29] that emerge along the dimensions of AI capabilities and areas of application (such as processes or tasks). AI capabilities, for example in terms of mechanical, thinking, and feeling intelligence [11] serve as decision anchors for determining AI deployment. Other approaches apply requirements to evaluate AI use cases [6]. Given the general-purpose nature of GenAI, approaches focusing solely on technology while excluding experienced workers fail to fully realize its potential.

3 Theoretical Background

3.1 Agents as the Unit of Analysis

GenAI-enabled agents often emulate workforce roles such as decision-making, planning, and execution. Applications in realistic scenarios—like customer service or project management—are essential for evaluating if these systems can match or outperform human agents [33, 34]. Use cases help assess how these systems function, interact with users and solve organizational challenges. However, agentic systems range from reflexive agents that automate routine tasks to prescriptive agents that make high-stakes decisions independently [33]. These systems have more autonomy, as they gain some control in making decisions and acting without human input [26, 33]. Understanding these distinctions is vital, as different agents play different roles in various forms of collaboration. AI agents complement human workers by managing routine tasks, enabling humans to focus on creative problem-solving. This division of labor helps assess AI's potential to match human agents across industries [13]. Understanding use cases for agentic AI requires a clear view of how human-AI collaboration unfolds, as the success of these systems hinges on how they interact and complement human workers. Trust, transparency, and task delegation are key to balancing autonomy with human oversight [35]. To fully grasp these dynamics, it is helpful to examine job roles, as they provide context for how different AI agents best complement human capabilities. Use cases grounded in these roles reveal how task complexity and collaboration dynamics shape the effectiveness of agentic systems [1, 34].

3.2 Collaboration Engineering

To address the given challenge, a structured reusable collaborative work practice is needed to guide practitioners in identifying GenAI potentials in knowledge-intensive processes. A reusable procedure has the potential to provide procedural guidance for GenAI agent identification, particularly in SMEs. Collaboration Engineering (CE) provides a design methodology for designing collaborative work practices, enabling practitioners to execute them without ongoing facilitator support. [36]. A collaborative work practice is a series of reusable collaborative activities performed by multiple teammates to achieve a group goal [38]. Groups that execute such engineered work practices can outperform groups that invent ad hoc collaboration procedures [34]. The CE approach is tailored to two unique roles – so-called Collaboration Engineers and Practitioners. Collaboration Engineers are familiar with the CE approach and have sophisticated collaboration skills. They have the capabilities to design a work practice regularly and deploy it to practitioners. Practitioners do not have collaboration expertise. They are skilled in their domain and familiar with the team's task. So, they can execute the work practice as a participant or as a facilitator who leads the group through the process.

Each work practice can be described in terms of its collaboration goal, group product (i.e. outcome), group activities (i.e., steps and instructions), group procedures (i.e. generate, reduce, organize, clarify, evaluate, build consensus), and thinkLets (i.e. named, scripted, re-usable, and transferable sequence of collaborative activities that serve as building blocks for collaborative process designs). To transfer engineered work practices to practitioners, Collaboration Engineers create so-called Facilitation Process Models (FPM) and an internal agenda. A FPM is a visual abstract overview of the whole process flow [4, 38]. The internal agenda serves as a plan for moderation and includes a detailed description of how collaborative activities should be executed. It also includes instructions and assignments, as well as an explanation of how collaboration tools (e.g. shared writing pages, voting) should be used.

4 Methodology

Our study follows the paradigm of action design research (ADR) [31], which is particularly well-suited for addressing practice-oriented problems in collaboration with industrial partners.

Organizational partner: Throughout the research process, we collaborated with a small and medium-sized enterprise (SME) to develop and test our artifact, leveraging interventions and reflective learning phases to address the practical challenge of identifying and selecting GenAI agents. The SME in focus is a well-established IT service provider specializing in a document management system designed to streamline the management and processing of documents critical to knowledge-intensive work. However, the rapid advancements in the field of GenAI pose significant challenges, particularly regarding the transformation of existing business processes and models.

The key activities of ADR involve building artifacts, intervening in organizational contexts, and evaluating outcomes through an iterative process known as the Build-Intervene-Evaluate (BIE) phases. This continuous cycle facilitates both the resolution of problems and the generation of knowledge, resulting in the formalization of learning [31]. Overall, we perform two main cycles of designing the co-creation process for identifying GenAI agents and conducting the ADR phases (Table 1).

In the ***first cycle***, the focus is on a problem-centric approach, starting with six interviews with domain experts to identify challenges in applying GenAI. A process for identifying GenAI use cases was developed and refined through simulations, partner walkthroughs, and an initial pilot test with practitioners. Challenges in deploying GenAI agents were aggregated, and core requirements were derived from interviews and literature, leading to the initial design of a co-creation process for identifying GenAI agents. The ***second cycle*** shifted to a solution-driven design, addressing specific challenges and characteristics of GenAI agents. Based on the findings from cycle 1, a process for designing and identifying GenAI agents was created, tested through additional simulations and walkthroughs, and validated with practitioners. Insights from these evaluations informed iterative improvements, resulting in a revised facilitation process model, a description of agent pattern components, and practical guidelines for integrating GenAI agents into organizational contexts.

Table 1. Overview of the applied ADR approach

Phase	Steps	Results
	Cycle 1	
I) Problem Formulation	• Expert interviews (n_{total} = 6) and literature review	• Need for a collaborative process
II) Building, Intervention and Evaluation	• Designing a process for identifying GenAI use cases. • Evaluation via simulation (n=1), walkthroughs (n=4), and pilot tests (n=12)	• Core requirements from interviews and literature • Initial design of the co-creative process
III) Reflection and Learning	• Reflecting on the initial design of the co-creation process of identifying GenAI agents	• Challenges in identifying agents by problems and processes • Understanding GenAI as agents and co-workers needed
	Cycle 2	
I) Problem Formulation	• Aggregating challenges and particularities of GenAI agents	• Need for facilitation guidance in exploring applications and describing agents
II) Building, Intervention and Evaluation	• Refining the process for identifying GenAI agents • Simulation (n=1), walkthrough (n=7), and validating the design within a pilot test with practitioners (n=8)	• Refining and extending the co-creation process for identifying GenAI agents (GenAI-CoP)
III) Reflection and Learning	• Evaluating the final design for GenAI agent operationalizability	• Thinking in smaller parts (e.g., prompts)
IV) Formalization of Learning	• Generalized requirements for designing a co-creation process • Facilitation process model and corresponding moderation plan for identifying GenAI agents • GenAI agents pattern components as a blueprint of the group product (outcome) for describing GenAI agents	

5 Designing a GenAI Agents Co-Creation Process

In the following sections, we describe our two design cycles in more detail and reveal the formalized learnings that we have made along the ADR approach.

5.1 Cycle 1

Problem Formulation. To better understand the underlying needs and challenges of utilizing GenAI technologies within the SME's document management system, we conducted a qualitative interview study by approaching six domain experts and system users (*Practice-Inspired Research*). The interviewees were briefly introduced with the basics of GenAI and exemplary applications and prompts. Through investigating the qualitative data, we identified initial ideas for building GenAI agents: *"I know this letter exists; it was five years ago. If I enter a few keywords, the AI could understand the content and show me the relevant text."* (Interview 04). Interviewees focused on GenAI as a chance to automate recurring tasks, however collaborative forms of GenAI agents such as "co-pilots" remained scarce: *"If an AI could automatically handle this and allow you to say, "Every quarter, I can check how many applications I received for such positions, for the individual job postings, for this Product Owner role or similar," then that would already be helpful to do."* (Interview 01). However, when discussing the potential applications of GenAI agents, the interviews emphasized the challenges and limitations of such technologies. For example, the use cases for GenAI may depend on the user's expertise and individual needs: "*For example, for me, this would be helpful because I don't have that much experience with applications. I could probably figure it out, but it would take me a bit longer than [a colleague]"* (Interview 01). In addition, the challenge lies in ensuring the completeness of information, as well as addressing the need for human intervention to provide additional context and fill in gaps that automated systems may not capture: "*The challenge is that we often have to revisit many items because we need to add something, as it's not always clear from the document—for example, how many hours are actually involved in this case*?" (Interview 01). Interviewee 04 added: "*Suggestions would be safer for me ... Cleaning up afterward sometimes takes longer than doing it yourself from the start*.". Overall, we recognized that system users struggle to imagine potential use cases and describe their ideas in their own words.

As a result of this phase, we identified the critical need to involve domain experts in a collaborative process aimed at identifying, describing, and prioritizing the development and application of GenAI agents.

Building, Intervention, and Evaluation. Based on the interviews' results and our resulting problem statement, we developed an initial design for a collaborative process. We derived initial requirements from the literature of collaborative engineering that explain what a co-creation process for identifying GenAI agents should look like. Engaging domain experts and empowering users to design GenAI agents with contextual understanding addresses *R1* (*Domain Knowledge*). A problem-driven approach, which involves breaking processes into smaller parts and identifying opportunities for augmentation or partial automation is central to *R2* (*Problem-Solution Pairs*) [10]. To support non-AI experts, a clear and accessible framework, such as a pattern-based format, was developed, aligning with *R3* (*Outcome Format*). Finally, fostering alignment among participants to ensure shared understanding, prioritization, and consistent communication is key to *R4* (*Collaborative Outcome Alignment*).

To refine the preliminary co-creation process, we began with a design simulation (n=1) of the GenAI-CoP, followed by a walkthrough session with facilitators, including moderators and GenAI experts (n=4). These activities provided critical insights to enhance the process design and evaluate whether GenAI-CoP could address the identified challenges effectively. This iterative effort resulted in a structured step-by-step guide for collaboration.

The initial process began with assessing the current status and defining the overall goals. Participants then identify problems and pain points in a chronological sequence, followed by brainstorming potential solutions. Problems and solutions were grouped into problem-solution pairs, which helped clarify the scope and focus of subsequent discussions. The next step involved defining goals, determining technological components, and establishing the balance between human and AI agency. Finally, participants describe their envisioned GenAI agents using a structured framework that captures key aspects such as goals, processes, problems, solutions, prompts, technological details, business value, and scalability. A pilot test with practitioners (n=12) validated this process, offering further refinement and confirming its practical applicability.

The participants valued the usefulness and clarity of the initial pattern blueprint. However, they stated that *"You first had to familiarize yourself with the framework before you could work on it."*. Additionally, they struggled to describe the process and task component: *"I found it somewhat challenging to fill this component. The connection to the other components could be made stronger. For example, this component [process component] could become part of the problem-solution pairs."*.

Reflection and Learning. The first design cycle provided valuable insights into the challenges of identifying potential GenAI agents within SMEs. Initial efforts, such as interviews, proved insufficient for engaging users in ideating GenAI use cases. Participants had difficulty articulating their needs due to limited GenAI knowledge and the complexity of designing agents. Users emphasized critical factors, including the necessity for human control, contextual understanding, and managing incomplete data. Furthermore, while GenAI's potential to automate tasks was acknowledged, the lack of hands-on experience constrained users' ability to envision collaborative, co-pilot applications.

An initial structured collaborative process, grounded in principles of CE, emerged as a more effective approach. The use of a pattern-based blueprint as a format for the collaborative outcome —incorporating goals, tasks, problems, solutions, prompts, and human-AI roles—enabled systematic exploration of use cases. This process also highlighted a key realization: the introduction of GenAI agents implies a shift in job roles, as the agents themselves take on distinct responsibilities. Initially, the focus was on understanding problems and processes; however, the complexity of mapping GenAI capabilities to specific processes became apparent.

5.2 Cycle 2

In cycle 2, our focus shifted from following a use case-driven approach to an agent-centric design of GenAI-CoP.

Problem Formulation. Reflecting on the first design cycle and its preliminary results, we identified several key challenges and limitations in our design approach that extend our understanding of the underlying problem. First, users expressed skepticism about GenAI's practical value, pointing to its dependency on contextual information and its inability to fully replicate human judgment. This skepticism was compounded by participants' limited experience with GenAI systems, making it difficult for them to explore potential uses or envision meaningful, solution-oriented applications. Hence, the second cycle must address the conceptual shift from perceiving GenAI as an abstract technology to recognizing it as a concrete agent or co-worker capable of undertaking specific tasks.

A major challenge was the need for a structured, agent-centric approach that encourages users to *"think in agents"* and view GenAI not just as a tool but as a collaborator with distinct roles. This requires breaking down problems into smaller, actionable components and delegating these to agents while also aggregating multiple dimensions into coherent agent designs. Moreover, aligning on and prioritizing the development of GenAI agents proved challenging due to varying expertise levels and operational needs among participants. Participants also struggled with describing and conceptualizing GenAI agents precisely, often lacking the necessary frameworks or technical language to articulate their requirements effectively.

These insights underscored the inadequacy of traditional problem-centric approaches in identifying and designing GenAI use cases. To address these issues, the second design cycle shifted toward a solution-centric perspective, focusing on the unique characteristics of GenAI.

Building, Intervention, and Evaluation. Based on the insights gained from the first cycle, we revised the initial requirements and design of GenAI-CoP to address identified challenges. To mitigate participants' lack of AI experience, we introduced an onboarding session that combined an introduction to GenAI agents with hands-on practice, aiming to establish a baseline level of AI literacy. To enhance the effectiveness of the co-creation process, we divided it into three parts conducted over two days, allowing participants to experiment with a GenAI agent between days. During this time, they explored GenAI tools and elaborated task descriptions, which became integral to the identification of agents by decomposing tasks and helping to specify the envisioned agents more precisely. Additionally, we refined the outcome format by revising the agent pattern blueprint and removing high-level fields such as business value and scalability to make the framework more tangible and actionable for domain experts. The updated design underwent a multi-stage evaluation process, including a simulation within the collaboration engineering team, a walkthrough with process facilitators, and a pilot study involving eight practitioners, ensuring iterative refinement and validation.

In the pilot study, we left out the initial two phases to avoid redundancy, as we introduced the practitioners within the first pilot test and collected task descriptions. While in the first cycle, we applied a problem-driven approach, we emphasized the role of GenAI agents as co-workers by discussing job roles and task descriptions. Within a short survey, the practitioners stated that they "*were able to discuss very specific use cases*". Furthermore, the results of the process "*are appropriate and allow prioritization*". While the participants were active during the discussion in the main room, one of the break-out rooms "*was very quiet with us and there wasn't much communication*". The comments helped us to revise the group work to make it more interactive and facilitate discussions.

Reflection and Learning. The evaluation process provided valuable insights into elaborating the operationalizability of the identified GenAI agents. Practitioners struggled to think in smaller, modular components, such as task descriptions and job roles, which are critical for specifying and delegating tasks to agents effectively. This revealed the need for a structured approach to help participants conceptualize agents in a more granular and actionable way. The process also emphasized the importance of transitioning from abstract agent designs to concrete, implementable solutions that can be feasibly operationalized.

6 Formalization of Learning

We formalized our learnings and consolidated them into a refined design for the co-creation process for identifying GenAI agents (*GenAI-CoP*). The resulting artifact includes the key components: design requirements, a facilitation process model (FPM), and a delegation format (i.e., *GenAI agent pattern blueprint*).

6.1 Requirements for the Co-Creation Process

After defining the initial requirements for the design of the collaborative process in the first cycle, we extended and refined these along the second cycle and after moving back and forth in the literature. Fundamentally, the designed collaborative work practice should incorporate key requirements from GenAI and CE literature alike to ensure high team performance and collaborative outcomes of high quality. It emphasizes the active involvement of domain experts, particularly knowledge workers, to leverage their expertise and contextual knowledge. A shared understanding among stakeholders is fostered to align outcomes and provide clarity on goals and the roles of the identified agents. Moreover, collaborative process guidance ensures a structured focus on developing both the content and agents involved. Additionally, the process enables participants to prioritize GenAI agents, facilitating a frictionless transition to implementation.

However, through reflection on our design, we expanded these fundamental requirements to include GenAI agent-specific needs. Table 2 outlines the core design requirements (DRs) that the process is intended to fulfill.

Table 2. Design requirements

ID	Requirements	Description
DR01	*GenAI knowledge*	The process should provide fundamental GenAI knowledge, including basic concepts and techniques (e.g., prompt engineering) [15, 25], to enhance AI literacy and ensure that subject matter domain experts without prior AI experience can actively and effectively participate.
DR02	*Agent-centricity*	The process should enable participants to perceive GenAI agents as collaborative and agentic co-workers [1, 34], fostering an understanding of their roles and contributions within the team dynamic.
DR03	*Agent exploration*	The process should enable hands-on exploration through interactive tools and prototypes, allowing users to practice and experiment with creating and refining GenAI agents and prompts [18].
DR04	*Delegation format*	The process should provide an outcome format [17] that effectively and intuitively describes the agent, ensuring clarity in its roles, capabilities, and interactions.
DR05	*Task breakdown*	The process should package facilitation guidance to help participants focus on the collaboration task [36]. It should enable the decomposition of tasks and processes into smaller, manageable parts, making them suitable for automation by GenAI agents while maintaining clarity and coherence in the overall workflow.

6.2 Facilitation Process Model of the GenAI CoP

Given the prior design requirements, we developed and refined a collaborative work practice. This work practice, GenAI-CoP, was instantiated based on an abstracted facilitation process model (FPM, see Fig. 1) that illustrates the steps (*S*) that practitioners (in the role of facilitators respective practitioners) have to proceed. Overall, the process spans three main phases and includes one homework in between phases two and three.

In the *first phase*, facilitators must prepare by providing a GenAI tutorial and access to GenAI tools (S0). The facilitators introduce the main concepts of GenAI (S1), provide prompting guidelines, and offer working examples to enable knowledge workers (S2) to effectively explore GenAI in the later phases (**DR1**). The *second phase* includes the work process and GenAI agent exploration (**DR3**). The participants test GenAI tools while being guided by the facilitators and the IT experts (S3). Afterward, the participants brainstorm initial ideas of GenAI usage (S4), which are then merged by applying the concentration thinkLet (S5). After parts one and two, which should happen within one day, the participants are tasked with a homework assignment (S6). Each participant should apply GenAI tools such as ChatGPT or Microsoft Co-Pilot at their workplace to elaborate specific task descriptions that describe what tasks GenAI agents should perform (**DR5**). Within the *third phase*, the elaborated task descriptions are first collected (S7) and then merged and clustered into GenAI job roles (S8) (**DR2**). The resulting GenAI job roles are then prioritized based on the CheckMark thinkLet (S9). The prioritized job roles lay the foundation to document GenAI agents utilizing the GenAI pattern blueprint (Section 5.3) (**DR4**).

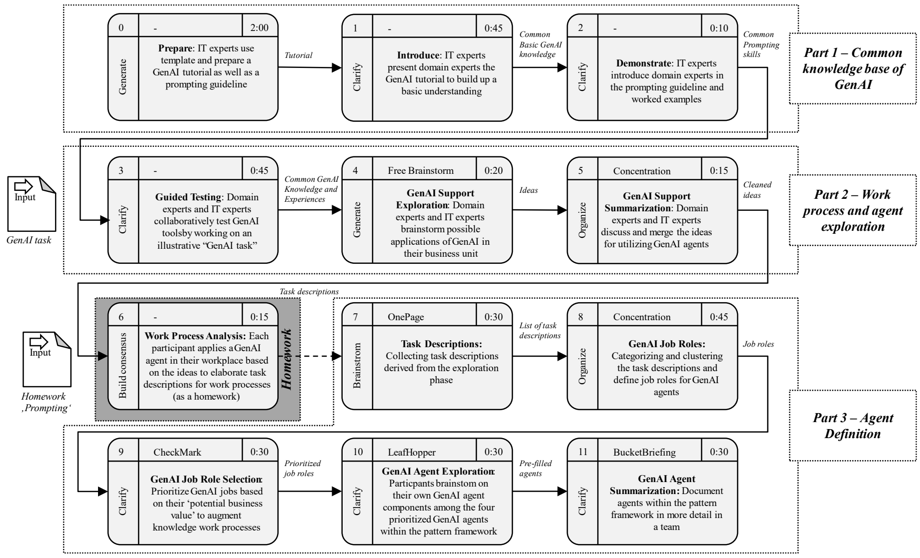

Fig. 1. Facilitation process model (FPM) for GenAI-CoP

6.3 Group Product – GenAI Agent Pattern Blueprint

As part of our iterative design approach, we derived a *GenAI Agent Pattern Blueprint* (Table 3) guided by the DRs and the process model. Practitioners participating in the GenAI-CoP collaboratively produce descriptions of GenAI agents as their group deliverable. The blueprint is a structured and systematic blueprint to define and refine GenAI agents, addressing the challenges non-AI experts face in conceptualizing and describing these systems. The blueprint comprises several interconnected components. *Goals* define the overarching purpose of the agent, specifying what the agent is designed to achieve, for whom, and for what purpose. For instance, an analyst agent's goal is to generate analyses, visualization, and reports. *Task descriptions* break down the processes and tasks that the agent automates or supports, facilitating a granular understanding of its operational scope. For example, the analyst's task is to provide status reports every Monday. *Problems* identify existing challenges in current workflows, while *solutions* outline how GenAI can address these issues. *Instructions*, including prompts and technological aspects (e.g., available data, context) provide actionable examples of how identified problems might be addressed, highlighting data requirements, and technical prerequisites. For example, "create a status report on all open applications". Finally, *human control* and *AI automation* delineate the respective roles and responsibilities of humans and AI, ensuring clarity in task delegation and operational boundaries. From the literature, we know that there are multiple variations of different forms of human-AI interaction and various degrees of automation. For instance, human-in-theloop describes that human input is being integrated into the AI model [21]. When humans remain in control, they are only being supported by AI systems to become more productive but humans make the final decision [5, 28]. These variations are important when developing agents.

Again, the structured blueprint addresses several previously mentioned DRs. First, it addresses the need for a tangible *delegation format* (**DR04**) by offering a clear mechanism for defining task responsibilities between humans and AI. By encouraging participants to decompose complex processes into manageable components, the framework directly supports *task breakdown* (**DR05**), making the design process more precise and actionable. Moreover, the framework promotes an *agent-centric perspective* (**DR02**), helping participants conceptualize the GenAI agent as a co-worker with distinct roles and responsibilities.

Table 3. GenAI agent pattern blueprint

Component	Guiding Questions
Goals	What is the overarching goal of the GenAI agent? What, for whom, for what purpose?
Task descriptions	Which processes and tasks are automated or supported by AI, and in what way? (Break-down in subtasks)
Problems	What problems and challenges exist in the current process?
Solutions	How can the problems be solved? How can GenAI be utilized?
Instructions	What might an example prompt look like for the identified problem? What data is required? What prerequisites need to be established? What additional technical specifics are necessary (e.g., RAG technology)?
Human Control	What tasks and responsibilities does the human take on and remain?
AI Automation	Which tasks are automated or supported by AI, and in what way?

7 Discussion, limitations, future research

Despite the great potential of GenAI to transform businesses and increase productivity, organizations particularly SMEs often struggle to identify and describe specific GenAI agents for integration into their processes and products [27]. Hence, this ADR project [31] developed a ***reusable co-creation process for identifying GenAI agents*** (GenAI-CoP) in cooperation with an SME aiming to transform their document management system through GenAI. Recognizing that the fundamental challenge lies in fostering a mindset shift from *thinking in use cases* to *thinking in agents*, we adopted an agent-driven approach. Our goal was to empower non-AI domain experts to perceive GenAI not merely as a tool but as agentic and autonomous co-workers. To achieve this, we designed and evaluated the co-creation process through two iterative cycles, including pilot tests with practitioners. The GenAI-CoP design introduces domain experts to GenAI, enabling them to explore its potential, and facilitates the derivation of specific GenAI agents tailored to job roles and task descriptions. As a result, our study derived design requirements for the co-creation process, outlined the process as a facilitation process model and provided a GenAI agent pattern blueprint to document agents as a collaborative outcome format.

Our theoretical contributions lie at the intersection of design science and use case identification and assessment. Concerning design science, we adapt the ADR method [31] to design a co-creation process in close collaboration with an SME. Our study shows how knowledge from collaboration engineering and design science can synergistically inform the design co-creation processes. We suggest that our approach is applicable not only in other departments of the partner organization but also across various knowledge-intensive domains such as customer support or sales. In terms of contributions to the literature on the use case and particularly the applications of state-of-the-art technologies such as GenAI [2], we shift the focus toward defining jobs and tasks rather than discussing and assessing use cases [10]. Thus, our design is novel concerning the incorporation of the concept of agency and autonomy [1, 33]. We redefine the identification of GenAI potentials as a structured process of task delegation to AI systems, requiring systematic development and formalization of job roles by domain experts.

Practitioners benefit from the developed GenAI-CoP by using the design as a blueprint for implementing the process and documenting GenAI agents. The process addresses the peculiarities of GenAI and large language models such as the high interactivity and the higher agency by enabling exploration, task breakdown, and a focus on agents as co-workers.

However, our study and approach also revealed several limitations. *First*, we did not validate the complete process within one pilot test to avoid redundancies in collaboration with the organizational partner. *Second*, our co-creation process does not specifically address the opportunities for multi-agent systems and agentic workflows [8]. Future research should consider the challenges of connecting multiple GenAI agents in workflow. This requires coping with greater complexity. *Third*, the process could be facilitated by technological tools, such as GenAI agents, designed to assist practitioners in exploring features, documenting and organizing tasks and prompts, and ultimately configuring and deploying agents.

In conclusion, our work provides a foundation for further research on GenAI and agentic AI that requires new approaches to enabling domain experts, to define forms of applications and document GenAI agents' design.

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