[ai]deation: GenAI-Based Collaborative Service Innovation

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Abstract

Many new services fail within the first year as businesses often launch services without a deep understanding of stakeholder needs. Recent advancements in generative AI, particularly Large Language Models (LLMs), have enabled the automation of creative tasks. In this work, we focus on the ideation phase of service development, aiming to integrate stakeholder perspectives early in the service development process through a novel human-AI collaborative role-based ideation method. Based on this method, we developed a software tool and an evaluation concept to support this approach. By tailoring the LLM's roles to meet specific stakeholder needs and incorporating diverse perspectives from the start, we encourage a more effective service development process, reduce the risk of poorly designed services, and facilitate coordination and understanding among stakeholders.

Keywords: Artificial Intelligence, Generative AI, Human-AI Collaboration, Large Language Model, Service Innovation

1. Introduction

Artificial Intelligence (AI) has made significant progress in producing human-like work, especially since the release of OpenAI's ChatGPT and other Large Language Models (LLMs) (Böhmann et al., 2024; Dell'Acqua et al., 2023; Lenharo, 2023; Wan et al., 2024). As AI mirrors human capabilities, the integration of AI into human work processes presents both challenges and opportunities, especially in knowledge-intensive or creative fields (Jöhnk et al., 2021; Memmert & Navid Tavanapour, 2023; Wan et al., 2024). Despite these advances, many organizations still face challenges in developing successful services (Momeni et al., 2023) because they fail to understand the real stakeholder perspective and miss the specific need of the customer. In this context, AI-driven solutions can help to effectively capture and integrate diverse stakeholder perspectives, accurately identify customer needs and iterate quickly enough to stay ahead of market demands. As outlined by Neuhüttler and Nägele (2023), AI can also support ideation in service innovation by preventing the development of existing ideas or by identifying untapped business opportunities. By selecting the most promising variants from many possible configurations and application scenarios, the speed and efficiency of service development can be increased (Kučević et al., 2024; Kuch et al., 2024; Neuhüttler & Nägele, 2023). In addition, this allows only the most promising ideas to be validated with real users reducing cost factors and time. However, AI-based tools and associated evaluations with users or in industrial applications are currently lacking. This gap highlights the need for practical applications and methodologies to test and validate these tools in real-world settings.

This paper presents a method that encourages active collaboration between the user and LLMs. Based on this method, we developed a software tool that increases the likelihood of relevant content being generated through

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intelligent role-specific prompting, using established methods from the field of generative AI.

Our contributions are twofold:

1. We demonstrate the practical applicability of our LLM-based method for active human-AI collaboration in the service innovation process.
2. We present an evaluation framework for evaluating this software prototype.

Through our work, we aim to establish a new paradigm for improving human-AI interaction and collaboration in the service innovation process. This effort not only addresses an immediate industry need but also paves the way for future innovations in the field of AI-based service design.

2. Related Research

2.1 Service Innovation

Service innovation involves reorganizing resources or altering structures and value co-creation processes within a service system (Edvardsson & Tronvoll, 2013;Kuch et al., 2024). This leads to the development of new practices that are beneficial and valuable to actors in a specific context (Lusch & Nambisan, 2015; Edvardsson et al., 2018) Therefore, when service firms innovate, they design resource integration mechanisms aimed at helping other actors, such as customers, to utilize and act on available resources in ways that generate value more effectively (Anke et al., 2020).

Despite the potential for both provider and customer, many services fail in the first year after market launch due to a lack of adoption (Momeni et al., 2023). Services differ from other sales goods, since they need a high degree of individuality to solve specific customer problems, a high degree of interactivity in the creation of services and a high degree of intangibility (Satzger et al., 2022). Individuality and interactivity lead to a need to organize the service innovation process as collaboratively as possible and to consider the perspectives of the stakeholders involved at an early stage. However, the intangibility of services makes it difficult to achieve a common understanding between the stakeholders for the joint innovation process, especially in the early phases, and is why many businesses do not understand the needs of the involved stakeholders well. This leads to their incapability to strategically develop new successful services. Consequently, both strategy and stakeholder's participation represent significant success factors of service development (Kitsios & Kamariotou, 2020).

Service (Systems) engineering is seen as a systematic procedure, which combines activities, methods, actors and tools for service development in a targeted manner (Böhmann et al., 2014). The discipline aims to increase the efficiency, effectiveness and reliability of the development process and supports service innovation through the methods, tools and frameworks it provides (Vikström et al., 2024). Bullinger et al. (2015) present one of these frameworks, which includes six phases: Ideation, Requirement analysis, Service design, Testing, Implementation and Market Launch.

In this paper, we focus on the ideation phase in particular. The ideation phase is the first step in service innovation. In it, suitable ideas need to be collected through available methods like workshops or customer inquiries. Requirements of internal and external stakeholders are analyzed, and a profitability check is performed. Relevant criteria are the fitting of strategy, cost effectiveness and feasibility, but especially the costumer and market perspective should be considered (Bullinger et al., 2015).

Since service innovation is an interdisciplinary field, it profits from the integration of relevant stakeholders as early as possible (Stickdorn, 2021). LLMs are, besides their other abilities, especially capable of giving inspiration and generating ideas, for which the required accuracy and precision are not as high as for later service innovation phases (Kuch et al., 2024).

In the service innovation process, there are different actors that recombine elements from both internal and external resources (Beverungen et al., 2018) as part of a service ecosystem by taking on specific roles. Generally, roles can be understood as activities that firms or individuals undertake, which are distinct, technologically separable and add value (Kambil & Short, 1994). They represent groups of behaviors anticipated from individuals in specific roles or positions (Knight & Harland, 2005). Actors can assume multiple roles (Anke et al., 2020).

LLMs can create new data from unstructured existing data. For this reason, with the necessary data, LLMs have the potential to personify these roles in a realistic way. With comparably little effort and costs, this could raise the efficiency and probability of success of the service development process by generating insights into stakeholders needs and requirements in the ideation phase. The potential of LLMs for service innovation has already been highlighted in several articles before (Böhmann et al., 2018; Böhmann et al., 2024; Neuhüttler & Nägele, 2023). With our contribution we offer a concrete use case for LLMs in service innovation.

2.2 Generative AI in Creative Tasks

AI is already being successfully used in various sectors of the creative industry, including marketing, book publishing and film (Amato et al., 2019). A range of AI methods support in the ideation process, including information creation, analysis and extraction, content enhancement and summarization (Anantrasirichai & Bull, 2022).

Within the field of generative AI, the role of LLMs, has become particularly notable due to their extensive knowledge base derived from massive training datasets. These models can handle a variety of natural language processing tasks, sometimes without needing any prior examples to learn from (Kojima et al., 2022), or with only very few examples (Brown et al., 2020). The use of LLMs can increase the productivity and quality of employees' daily work in various text-based tasks (Lenharo, 2023).

Moreover, the use of LLMs in creative processes is particularly promising (Wan et al., 2024). Recent experiments have shown that ideas developed with the help of an LLM are superior in terms of novelty and customer value compared to ideas developed by humans alone (Joosten et al., 2024). Additionally, individuals with access to an LLM have been found to outperform human groups in brainstorming sessions, as LLMs help to overcome well-known brainstorming problems, e.g. production blocks and social inhibitions (Bouschery et al., 2023). LLMs can facilitate the generation of new ideas by providing cognitive stimulation (Memmert & Navid Tavanapour, 2023).

However, there are challenges when LLMs are part of the ideation process. It has been observed that LLMs can increase the risk of 'free riding', where individuals take content and ideas without putting in any effort (Memmert & Navid Tavanapour, 2023). In addition, LLMs do not always provide relevant or even correct information and often produce overly generic answers (Salikutluk et al., 2023).

3. Research Approach

3.1 Role-Based Ideation

In ideation processes of all kinds and especially in brainstorming, it is advantageous to consider as many different perspectives as possible (Paulus & Brown, 2007). For this reason, creative methods such as the *Six Thinking Hats method* (Bono, 1999) or *the Walt Disney method* (Dilts, 1995) encourage users to systematically adopt different perspectives. This applies for the ideation phase of service innovation as well (Anke et al., 2020). In particular, the *Six Thinking Hats method* has shown its benefits for the innovation process in various experiments (Azeez, 2016; Göçmen & Coşkun, 2019). Furthermore, the Walt Disney method has also been successfully applied in different scenarios (Tausch, Nußberger, & Hußmann, 2015; Tausch, Steinberger, & Hußmann, 2015).

The Six Thinking Hats method is based on the division of thought into six roles, each of which is assigned a hat of a specific color. The white hat symbolizes analytical thinking and an emphasis on objective facts, whereas the red hat represents a more emotional perspective. The black hat is responsible for critical reflection, the yellow hat for an optimistic attitude, the green hat for generating new ideas, and the black hat for facilitating brainstorming. The Walt Disney method streamlines the approach of the Six Thinking Hats by reducing the number of roles to three instead of six: the roles of the dreamer, the critic, and the realist. The dreamer represents an optimistic person, the critic is a person who offers critical reflection, and the realist is a fact-based thinker. Depending on the design of the two methods, the roles are played by different people, or one person systematically goes through the roles one after the other.

Both methods are limited to the roles described and are therefore not suitable for mapping other company-specific roles. However, these company-specific roles can provide further important insights for the ideation process and ensure that customer needs are better recognized. . For example, Magnusson (2009) found that in the development of technology-based services, the perspectives of ordinary users, i.e., users with a lot of usage experience but little technical expertise, can lead to particularly innovative ideas. Including employee perspectives in the service development process can also contribute to a positive outcome (Mu et al., 2018).

3.2 Enhancing Collaborative Ideation with Generative AI

The use of LLMs enables the implementation of the above-mentioned roles from creative methods as well as company-specific roles in the form of AI personas. This is due to the ability of LLMs to imitate a wide variety of roles, when provided with sufficient information about a role, e.g., a description of that role in text form (Salewski et al., 2023). This allows the individual to benefit from the diversity of perspectives and roles without the need for multiple people having to take on the different roles, or for one person investing the time and mental effort to think their way into all the roles. While methods like the Walt Disney Method already provide some benefits in the innovation process when used in their intended form, assigning roles to an LLM entails further advantages; through extensive training, LLMs contain a broad knowledge that can be further extended and tailored to a specific context using methods like finetuning or utilizing knowledge stored in databases through retrieval augmented generation. This allows for the creation of LLM-based expert roles that provide viewpoints and questions based on an extensive knowledge base of contextually relevant data. This is particularly beneficial when there is a lack of human experts, and the human user has only little knowledge of the matter entailed by the respective role. Furthermore, integrating LLMs into the process enables the generation of fully data-based roles. For example, customer roles may be derived from previous customer surveys, thereby reducing insecurities and inaccuracies that may arise when relying solely on the human user's idea of a role.

The use of LLMs can therefore not only make the ideation process more diverse, but also reduce the human effort and dependency on the human's limited knowledge of the considered roles.

In the following, we propose a method to enhance collaborative ideation between a human and an LLM assistant (see Figure 1). The goal is to effectively develop viable ideas by simulating conversations with stakeholders who have different expertise and viewpoints.

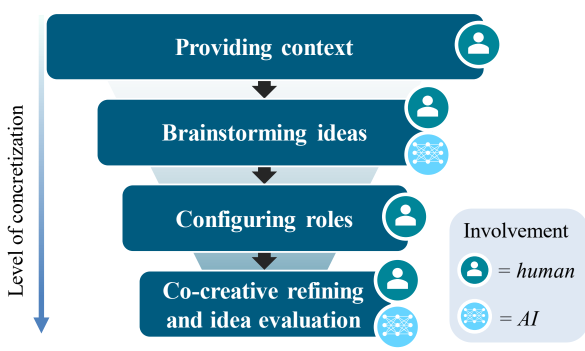

Figure 1. Proposed process steps of ideation: the level of concretization increases along the process until viable ideas are identified and refined.

(1) Providing Context

The first step is to provide context about the user and the general topic. This context can include an existing business model, but the goal might also be to develop a new business model from scratch. The more the LLM knows about the user's goals and background, the more specific and relevant its responses will be. Previous research indicates that LLMs create better and more relevant ideas when given more specific prompts (Lin, 2024).

Goal: *Target-orientation of LLM by improving the assistants understanding of the user's objective; increasing the relevance of assistant's responses*

(2) Brainstorming Ideas

In this step, the user should first brainstorm independently. This step is recommended to mitigate the risk of free riding. When the user encounters a creative block, they can request the assistant to generate additional new ideas. Ideas that have already been developed with the help of the LLM will further improve the LLM's understanding of the user's objective.

Goal: *Pool of ideas to start with; encouraging the user to not solely rely on the LLM*

(3) Configuring and defining roles

Next, the user configures the LLM assistant by assigning it a role. Depending on the problem statement, these roles can be derived from the Walt Disney Method, but also tailored specifically to the problem. In the context of service development, it is recommended to integrate a strong market and customer perspective in the ideation phase (Bullinger et al., 2015). Higher-level roles from the Walt Disney Method can be combined with more specific roles to create even more distinct roles. We hypothesize that assigning more distinct roles to the LLM will result in a greater variety of ideas.

Goal: *Finding roles and viewpoints (e.g., stakeholders) that are relevant to the problem and should be considered in the ideation process*

(4) Co-creatively Refining and Evaluating Ideas

The user then discusses the collected ideas with the assistant which assumes the previously selected role. We suggest that the user interacts with the LLM as if they were discussing a problem or idea with a colleague. The conversation can involve asking the LLM for feedback, examples, further refinement, potential pitfalls, and more. Incorporating the different perspectives during this on-going dialogue helps to refine the discussed ideas. Ideas that are deemed not viable by the user can be discarded. In service development, important evaluation criteria include the fitting of the strategy (e.g., when starting from an existing business model), feasibility, customer benefit and marketability (Bullinger et al., 2015). These criteria may also be integrated directly into the roles defined in step (3). The process can be stopped whenever the user is satisfied with an idea.

Goal: *Refinement and prioritization of collected ideas; identifying practical ideas by considering a variety of perspectives on the problem*

4. The [ai]deation tool

Based on the previously described ideation process, we developed a software tool called "[ai]deation" for idea generation and reflection, containing a configurable LLM-assistant.

4.1 Functionalities

The application contains two main functionalities that spatially divide the user interface (see Figure 2) into two sides: (1) Idea management and (2) Ideation assistant.

Idea Management

Ideas can be collected, edited, sorted, and prioritized in a list. Users can add their own ideas or ideas proposed by the assistant with a single click. The idea list is incorporated into the assistant's system prompt before a user request, allowing it to reference the user's ideas without needing explicit description in the chat. In addition, the assistant is informed about the currently selected idea; thereby we encourage a focused and efficient discussion.

To ensure that the software is well integrated into common workflows, it provides functionality to import ideas and export in MS Word format after an ideation session.

Ideation Assistant

Users can assign the predefined roles to the LLM. Optionally, the user can specify custom roles through a form. From a technical point of view the role definition is incorporated into the system prompt of the LLM. The user interacts with the (configured) assistant through a chat window. Pre-selected text suggestions are available to speed up interactions.

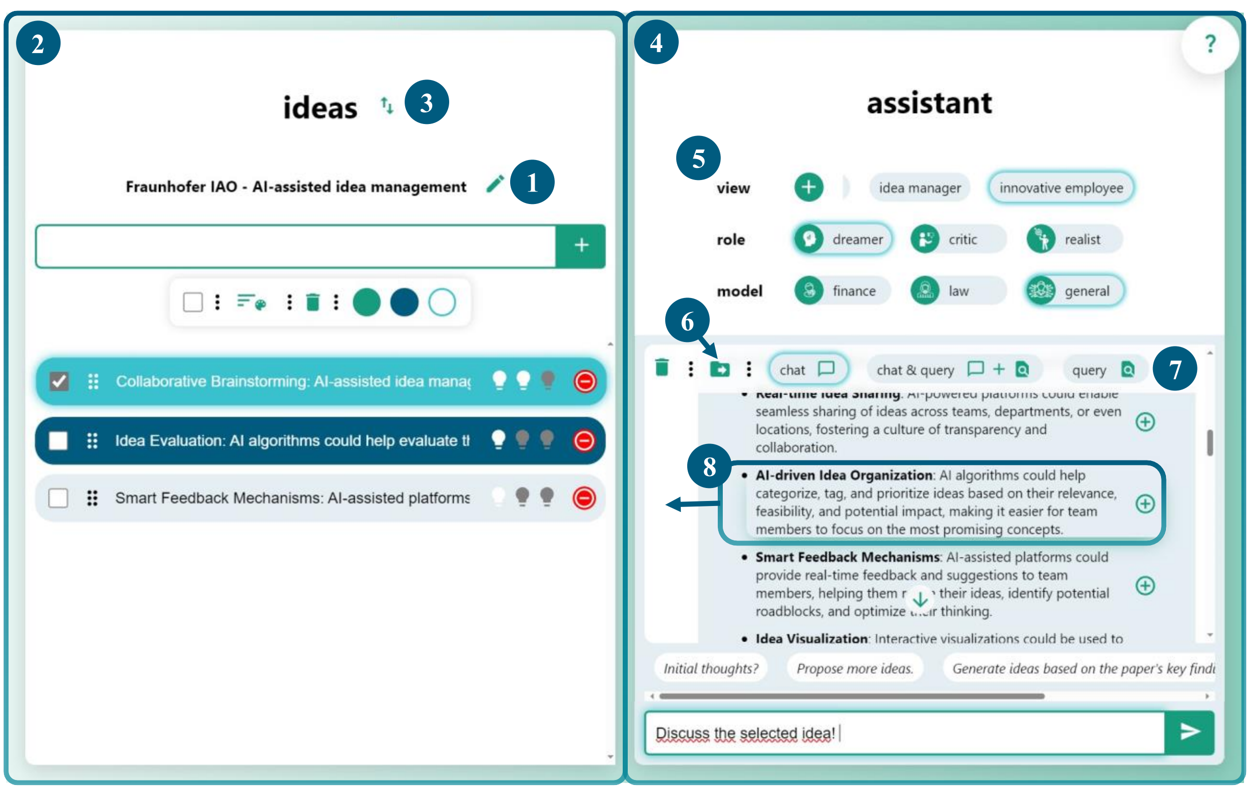

Figure 2. User interface of [ai]deation software: (1) providing context information, (2) idea management area, (3) import/export ideas/ a report, (4) ideation assistant, (5) configuring the assistant, (6) upload additional context information to database, (7) select a chat mode, (8) add ideas from the chat via one click.

4.2 Software Architecture

[ai]deation is built as a client-server application. It consists of a user interface *(frontend)* and a Python script *(backend)* that processes requests from the user interface. The frontend has been developed as a React web application. It implements the user interface that handles all necessary user interactions for the features described in 4.1 and sends requests to the backend, for example, questions from the user that need to be processed by the LLM.

The backend contains the LLM, in our case *Llama3 instruct 8B (AI@Meta, 2024)*, and a vector database (PostgreSQL with pgvector). When the user sends a chat message in the web application, the request is sent to a local web server as a HTTP POST request with a JSON payload. The message is then passed to the selected LLM, and the response is sent back to the web application as a text stream. The Streaming response returns text chunks to the frontend as soon as they are available, ensuring the message is displayed progressively rather than waiting for the complete response from the LLM.

To load the LLM's parameters, we use the library llama-cpp. In case the user uploads additional context data, an embedding model transforms the text documents into a numerical vector representation which is then stored in the database. This is necessary for context retrieval from the vector database: relevant text content is retrieved based on similarity to the (embedded) search query / user question. Subsequently, the retrieved context is added to the prompt for the LLM. For context retrieval, we use functionality provided by the library llama-index.

Figure 3 shows the overall software architecture of [ai]deation.

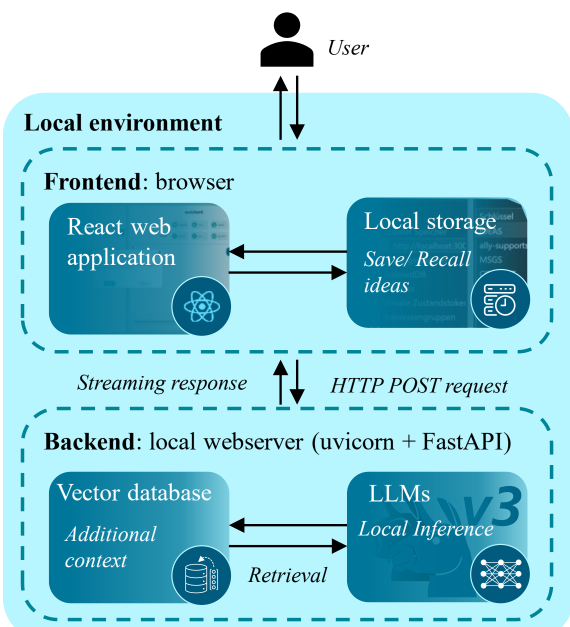

Figure 3. The software architecture of [ai]deation consists of the user interface (frontend), the LLMs and a vector database (backend).

5. Concept for Evaluation

As the general added value of using LLM in the ideation process has already been evaluated (Bouschery et al., 2023), the focus of the evaluation concept presented here is to demonstrate that the ideation tool offers significant added value compared to generic LLM applications due to the role-based, collaborative ideation method used. Initial discussions and test cases with various companies have shown the great potential of the method. For instance, a workshop with an elevator company demonstrated that the various stakeholder groups involved in the elevator's life cycle and essential for ideation can be effectively mapped using the specific roles. To formally evaluate the tool, we first aim to demonstrate the advantage of the tool over generic LLM applications in a laboratory experiment and then examine the effect of ideation within a company as part of an application study.

5.1 Laboratory Experiment

The experimental design of Bouschery et al. (2023) can be followed for the evaluation of the tool in the laboratory experiment. They use a single-factor between-subjects design to test the extent to which the use of a generic LLM can improve brainstorming. The test subjects were divided into three distinct groups. In these groups, the subjects either worked independently with and without the assistance of a generic LLM model or within a small brainstorming group without LLM support. We propose to extend this concept by another group in which one person works with the developed [ai]deation tool. The experiment design allows for the examination of the added value of the tool in comparison to classic brainstorming, as well as the advantages of the tool in comparison to the use of a generic LLM application.

To evaluate the results of a brainstorming session, we also follow the method used by Bouschery et al. (2023), in which not only the number of ideas is measured, but also the quality of the ideas. The quality is determined using a data-driven approach in which the edge weights of semantic networks are used as a measure of creativity (Toubia & Netzer, 2017).

5.2 Application Study in a Company

To ascertain whether [ai]deation can also be efficacious in real-world contexts within a company, one of two approaches can be selected, contingent on the specific circumstances within the company. The tool could be made accessible to every employee in the company, after which the innovativeness of the company could be gauged over an extended period. The innovativeness of a company can be quantified by comparing the innovative input of a company, such as employee education or R&D expenditure, with the innovative output, such as new services, patents, or trademarks (Alegre & Pasamar, 2018; Taques et al., 2021). In the case of our application study, it is anticipated that, although the input remains constant, the innovative output of the company will increase. If company-wide use is not feasible, it may be possible to provide access to the tool to a select group of employees. In this case, the innovativeness of the company can no longer be measured, as the effect of a few tool users on the company would be too small. Instead, the performance of the ideas developed with the tool should be evaluated and compared to other ideas in the company's innovation process. An evaluation of the product or service concept is particularly suitable here, as there are various methodologies that have been developed for evaluating products, service or smart services concepts (Freitag & Schiller, 2017; Neuhüttler et al., 2019). It can be reasonably assumed that ideas that have undergone a more sophisticated development process using the [ai]deation tool will be more readily transformed into superior service or product concepts.

6. Discussion

6.1 Theoretical Implications

The results of this paper show the potential of LLMs for service innovation. LLMs allow the early integration of stakeholder perspectives in the innovation process, which supports not only in considering the internal perspective, but also the external and market perspectives of service development at the same time. They offer ways to improve service innovation by giving structure to the ideation phase, which typically has a more creative focus.

By incorporating stakeholder perspectives early on, our methodology reduces the risk of potential development failures throughout the process. In the next step, the requirement analysis, the goal is to identify customer wants and needs, which we have already partially considered in the ideation phase. Same goes for the testing phase, where it helps us avoid unexpected backlash. All consecutive phases that integrate stakeholder perspectives also profit from using the presented method in the ideation phase. This can avoid development loops caused by impractical service ideas, increases efficiency and reduces development costs.

The presented method offers a new viewpoint on the existing roles in service development and leads to a paradigm shift in the service innovation process. Through the implemented roles, focus can be put on costumers and specific stakeholders more efficiently, which is crucial for service success.

In the context of industry 4.0 and big data, companies have big amounts of structured and unstructured data available. With LLMs' unseen capabilities of data analysis, this offers the potential to increase the reliability and validity of service innovation. Still, at this time, the reliability and validity of LLMs themselves cannot be guaranteed, which is why we focused on the ideation phase only. Here, consequences of possible failures are not as high as in later development phases, where the identified ideas are further evaluated and elaborated.

Overall, in this paper, we show how to apply the WD method in LLMs in combination with the service innovation process. We demonstrate the applicability of the method for active human-AI collaboration and present a framework for its evaluation. This offers a new cocreating setting for service innovation and promotes human-machine-cooperation.

This contribution highlights the strength of LLMs in supporting knowledge-intensive and creative fields and extends the literature on hybrid intelligence.

6.2 Practical Implications

Service development often requires balancing various interests since services are typically provided within an ecosystem (Vargo & Lusch, 2016). A basic characteristic of services is integration of external and internal resources. These resources belong to various stakeholders, who, as pointed out in this article, have various interests, requirements and needs in service development (Bullinger et al., 2017; Haller & Wissing, 2020)

Our method encourages companies to tailor the LLM's roles to meet their specific needs and consider relevant stakeholder in their service development process. By integrating diverse perspectives, such as customer or stakeholder viewpoints, early in the development, companies can create more target-oriented services while reducing the risk of poorly designed services.

Previous literature has shown AI assistance to increase the effectiveness of idea generation (Bouschery et al., 2023). As our method is designed for service development, we hypothesize an increased efficiency and reduced personnel costs in service development processes. This is also due to a decreased need for coordination among different human experts and stakeholders, as we emulate cognitive synergy between multiple human actors through LLMs.

Incorporating company-specific context with retrieval-augmenting generation ensures that the assistant's feedback and ideas are more relevant and derived from contextual knowledge rather than general knowledge of the LLM. This allows for more relevant, specific, and technical discussions where the general knowledge of an LLM may be insufficient. In addition, retrieval-augmenting generation reduces the risk of hallucinations, making responses from the LLM more reliable.

Bouschery et al. (2023) find that AI alone is more efficient at generating ideas of high quality compared to human-AI collaboration. There are also fully AI-based approaches which aim to emulate multi-agent collaboration to solve complex tasks (Wang et al., 2023). However, we intentionally focused on a human-AI collaborative approach.

7. Limitations and Future Research

Although the tool has been successfully employed in certain company contexts, a formal evaluation is still pending. Consequently, the precise added value of the tool in the service development process remains uncertain. Furthermore, the extent to which the use of different LLMs affects the tool's performance remains unclear. It is possible that certain LLMs are more effective than others in supporting idea generation. The initial case studies with companies have demonstrated that a simple description of the role as a prompt is insufficient for the LLM to portray the role in a credible manner, particularly in the context of highly complex and company-specific roles. Future research could investigate the extent to which techniques such as finetuning or retrieval-augmenting generation can be employed to enhance the LLM's ability to represent a specific role. The research results presented here also offer some other possibilities for future research. For instance, the evaluation method described in section 5 should be used to closer investigate the impact of the tool on the service development process.

Moreover, the evaluation of the tool can serve as a foundation for further investigation into the potential applications of generative AI and LLMs in the subsequent phases of the service innovation process. A particular focus should be placed on the design of successful human-AI collaboration while also emphasizing the specific conditions in these various phases. The tool presented in this paper provides an ideal foundation for research in this area, offering a multi-actor platform that can be further developed and on which humans and AI can create value cooperatively. In the future, this could result in a consistent tool that is applicable for the entire service innovation process. Adopting a design science research (DSR) approach in future research could generate valuable knowledge on the systematic design of LLM-based tools for service innovation, thereby bridging the gap between software development and scientific research.

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