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# Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models

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## Abstract

The use of transformer-based language models in artificial intelligence (AI) has increased adoption in various industries and led to significant productivity advancements in business operations. This article explores how these models can be used to augment human innovation teams in the new product development process, allowing for larger problem and solution spaces to be explored and ultimately leading to higher innovation performance. The article proposes the use of the AI-augmented double diamond framework to structure the exploration of how these models can assist in new product development (NPD) tasks, such as text summarization, sentiment analysis, and idea generation. It also discusses the limitations of the technology and the potential impact of AI on established practices in NPD. The article establishes a research agenda for exploring the use of language models in this area and the role of humans in hybrid innovation teams. (Note: Following the idea of this article, GPT-3 alone generated this abstract. Only minor formatting edits were performed by humans.)

## KEYWORDS

artificial intelligence, GPT-3, hybrid intelligence, innovation teams, prompt engineering, transformer-based language models

## 1 | INTRODUCTION: AI AND INNOVATION

Over the last few decades, we could observe numerous technological advancements in the field of artificial intelligence (AI), including algorithmic breakthroughs, benefits of digitalization in the form of inexpensive data collection and handling, open-sourcing of key technologies, and access to cloud-based services (Bleier et al., 2020; von Krogh, 2018). These advancements have increased the adoption of AI in a variety of industries and led to significant productivity advancements in operational business

functions. They could also enable a more data-driven and AI-based approach to innovation (Cockburn et al., 2018; Kakatkar et al., 2020) that could bear new possibilities to dramatically increase the productivity of new product development (NPD)—an endeavor much more challenging than increasing the efficiency of a production task (Bloom et al., 2020; Brynjolfsson et al., 2019).

Among the different types of AI, transformer-based language models may bear particularly interesting opportunities for an AI-augmented innovation process. They are a type of AI designed to process and generate (natural) language in the form of text and can be used for various tasks

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such as machine translation and text summarization, insight extraction, or generating creative output. This makes language models an especially interesting form of AI in knowledge-intensive work such as NPD. Examples of such models include Google's BERT or OpenAI's Generative Pre-trained Transformer (GPT-3). They not only reached human-like language understanding abilities (Zhang et al., 2021) but also feature an intuitive way of user interaction based on natural language. Transformer-based language models have advanced so much that publishers now use them to write entire articles (The Guardian, 2021) or, for example, the Parliament of Finland (Eduskunta) (2021) includes them as a member of parliamentary panels to complement humans in debates. Furthermore, numerous companies have started to deploy such models to tackle innovation challenges (see, e.g., Toews (2022) for an overview of companies providing products and services based on transformer-based language models). Examples include "Hebbia", which built a search engine to tap into vast amounts of unstructured data and extract relevant insights; "Inceptive", which applies language models to the development of RNA therapeutics and vaccines, or "CopyAI", which uses the generative abilities of transformer-based language models to automate writing a marketing copy.<sup>1</sup> These examples already indicate the opportunities to use this class of AI for automation and efficiency improvements along the stages of the innovation processes.

At the same time, transformer-based language models ask us to reconsider many established practices in NPD. For example, their creative abilities question common practices of how good ideas are created, like using creativity techniques or other divergent thinking tools. Specifically, the role of humans in NPD will change as AI takes on more tasks. So how will innovation teams deal with AI-generated and AI-co-created ideas? How do we address the fear of human experts being replaced by a machine? Will designers be reduced to "prompt engineers", that is, just designing the task given to an AI instead of the product or component? Augmenting human innovation teams with AI hence calls for investigating many aspects of jointly working with AI rather than only human colleagues.

With this catalyst, we hope to spark a discussion on how transformer-based language models will impact innovation and how this affects extant research in the field of NPD. The following section will briefly introduce the basic technology behind transformer-based language models. We then present the AI-augmented double diamond as a framework to guide our exploration of transformer-based language models for innovation. Next,

<sup>1</sup>The respective websites for these examples are <https://www.hebbia.ai>, <https://inceptive.life>, and <https://www.copy.ai>.

### Practitioner points

- Transformer-based language models like GPT-3 are a powerful type of AI that can perform various tasks during an innovation process like text summarization, sentiment analysis, insight generation, or idea generation at an incredible scale.
- Such technologies support the exploration of larger problem and solution spaces and can augment humans to improve innovation performance.
- Artificial intelligence and humans will increasingly work together in a form of hybrid intelligence, which calls for a re-evaluation of how we approach and manage innovation.

we discuss several concrete examples of utilizing these models in typical tasks of an innovation project, using the GPT-3 algorithm, a powerful and easily accessible transformer-based language model. We use these examples to develop a set of research questions that arise from integrating such AI into NPD teams, also discussing the limitations of such technologies. Our goal is to spark further debate and research on the opportunities, limitations, and managerial implications that emerge when artificial and human intelligence are combined to solve complex innovation tasks in a way that none of them alone could have accomplished.

## 2 | TECHNICAL BACKGROUND: LANGUAGE MODELS

Transformer-based language models are a special kind of AI used for natural language processing (NLP), which is a range of computational techniques for analyzing and representing naturally occurring texts to achieve human-like language processing (Liddy, 2018). In general, NLP is not new to innovation management. Previous research has explored such techniques in the area of text analysis (text mining) and how they can be applied to innovation processes (Antons et al., 2020). Whereas earlier models have typically been very task-specific, newer NLP technologies can take on multiple innovation-related tasks. Especially so-called generative or transformer-based language models have recently moved to the center of attention. Many transformer-based language models are autoregressive models (e.g., GPT-3), meaning they predict a word based on its preceding words in a text. NLP has

TABLE 1 Selected scientific milestones in natural language processing (NLP)

Reference	Title	Milestone
Garay-Vitoria and González-Abascal (1997)	Intelligent word-prediction to enhance text input rate (a syntactic analysis-based word-prediction aid for people with severe motor and speech disability)	Introduces word-prediction based on a syntactic analysis
Bengio et al. (2003)	A neural probabilistic language model	Introduces neural networks for calculating probability functions for word sequences
Mikolov et al. (2010)	Recurrent neural network (RNN) based language model	Introduces RNNs for language modeling
Graves (2013)	Generating sequences with RNNs	Introduces long short-term memory (LSTM) RNNs for text prediction
Bahdanau et al. (2014)	Neural machine translation by jointly learning to align and translate	Introduces attention mechanisms
Vaswani et al. (2017)	Attention is all you need	Introduces the transformer architecture
Devlin et al. (2018)	Bert: Pre-training of deep bidirectional transformers for language understanding	Introduces large bi-directional transformer-based language models
Radford et al. (2018)	Improving language understanding by generative pre-training	Introduces a line of generative pre-trained language models
Brown et al. (2020)	Language models are few-shot learners	Highlights few-shot learning capabilities of large language models

seen continued progress over the past decades with a trend toward larger and more complex models rapidly increasing their capabilities—from the mere suggestion of related words (Garay-Vitoria & González-Abascal, 1997) to state-of-the-art models that can produce full newspaper articles indistinguishable from human-written text (Brown et al., 2020). For readers interested in technical details and developments leading to transformer-based language models, Table 1 presents an overview of important technical milestones in this field.

The “Transformer Architecture” introduced by Vaswani et al. (2017) provides the basis for most state-of-the-art language models. These models can take the context of the processed words into consideration, which allows for a more nuanced understanding of related words and concepts. Because the capabilities of these models significantly improve with model size (Brown et al., 2020; Radford et al., 2019; Tamkin et al., 2021), the rapid increase in model sizes—newer versions, such as GPT-4, are expected to have 100 trillion parameters—has severe implications for the usefulness and applicability of transformer-based language models for innovation tasks.

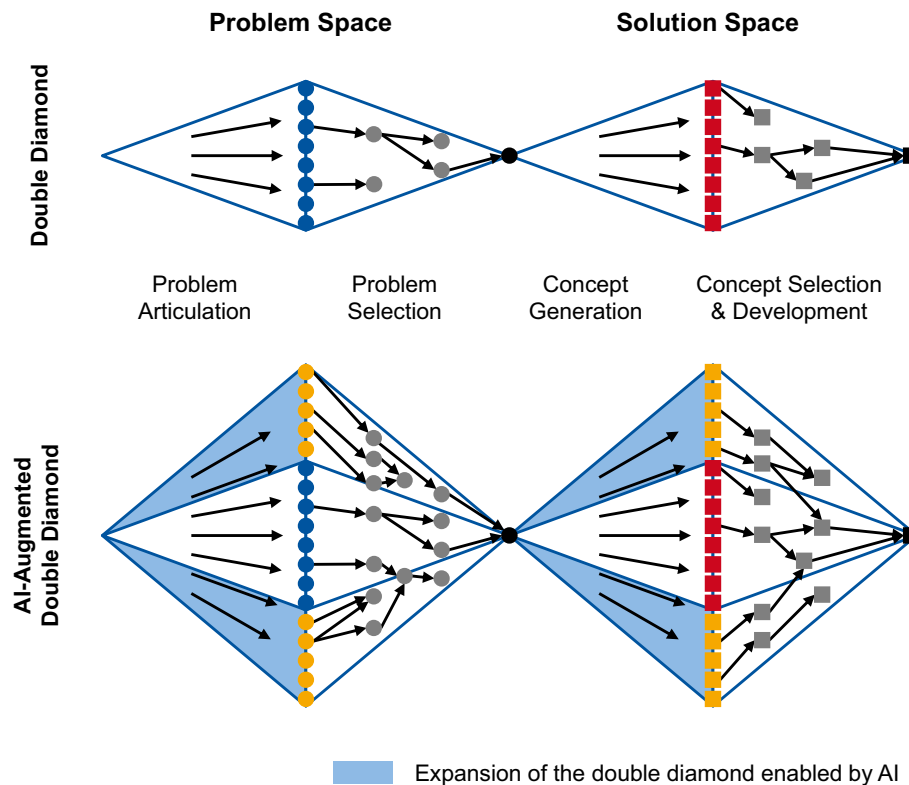
### 3 | AI-AUGMENTED KNOWLEDGE-BASED PRACTICES

Knowledge is a key resource central to a firm’s innovation activities (Crossan et al., 1999). A large body of

literature has conceptualized innovation management as a knowledge-based practice (e.g., Chung & Lee, 2020; Silva et al., 2018). Such practices are inseparably connected to language—be it talking to a colleague, listening to a lecture, or reading an article. Understanding language grants us access to a plethora of knowledge. This makes language models an especially interesting form of AI for knowledge-intensive work such as NPD.

#### 3.1 | The AI-augmented double diamond framework

To structure our exploration of potential use cases of how transformer-based language models can augment human innovation teams in the future, we refer to the double diamond framework (Figure 1, upper picture). Popularized by the design thinking community since the mid-2000s (Design Council, 2022), it builds on the works of Guilford (1956), who is generally attributed with originally making the distinction between divergent and convergent thinking. Innovation processes consist of a sequence of steps where innovators first explore a wide range of problems and opportunities to then decide on adequate (technical) solutions to the given problems (Marion et al., 2023; Marion & Fixson, 2019). In both stages, innovation teams perform divergent and convergent tasks. Successfully navigating through these processes requires building on substantial amounts of



**FIGURE 1** The original double diamond framework (above), as conceptualized by Marion and Fixson (2019), and the artificial intelligence (AI)-augmented double diamond framework (below)

existing knowledge and ultimately generates new knowledge. Building on the conceptualization of innovation processes as a double diamond, we present the AI-augmented double diamond (Figure 1, lower picture) as a framework that highlights how AI and especially transformer-based language models can be particularly useful for fostering divergent processes and help to explore larger problem and solution spaces.

By expanding the problem and solution spaces in which NPD teams can operate, language models create an opportunity to access and generate larger amounts of knowledge, which in turn results in more possible connections of problems and solutions. This should ultimately lead to qualitatively superior solutions and higher innovation performance. In the following, we discuss specific applications of transformer-based language models in NPD, highlighting their potential to improve innovation productivity by augmenting human innovation teams in exploring larger problem and solution spaces. For our exploration of exemplary use cases, we utilize the GPT-3 algorithm. This language model has fundamentally shaped the AI space in recent years (Zhang et al., 2021). It was first introduced in 2020 and is offered by OpenAI, a Silicon Valley-based startup founded in 2015. In December 2022, many media reports about ChatGPT, a chatbot built on top of GPT-3 and fine-tuned

with supervised and reinforcement learning techniques to generate detailed responses on a large variety of topics, made GPT-3 known to a larger audience. For readers interested in replicating our use cases, we provide the technical parameters used to tune the model in a web appendix to this article (Appendix A1 has more information on how to access and interact with this AI model).

### 3.2 | Exploring problem spaces with AI

Exploring problem spaces includes building on existing knowledge to identify opportunities for innovation. To do so, innovation teams employ knowledge-based practices such as knowledge capitalization and knowledge spanning, which, at their core, help to access knowledge that exists either within an organization or in its network (Silva et al., 2018). To make such existing knowledge usable, innovators have to extract knowledge that might be coded explicitly or implicitly in a given knowledge base. Members of an innovation team can then further process the extracted information, internalize it, and convert it into new knowledge that their firm can then use in their innovation processes.

Typically, extracting vast amounts of knowledge is rather labor-intensive and not easily scalable because

much knowledge is encoded in unstructured data that is still difficult to process automatically (Fan et al., 2012) and, therefore, involves humans manually reading and extracting information and knowledge. Earlier machine learning (ML) models have already automatized parts of such processes. ML algorithms perform well on a variety of pattern recognition tasks that are relevant for knowledge extraction. These can range from detecting patterns in visual data, for example, for quality control or analyzing technical samples of an experiment, to identifying novel ideas in online communities (Christensen et al., 2017) or customers with lead user characteristics (Kaminski et al., 2017). Transformer-based language models like GPT-3 are the next level of technology for such knowledge extraction practices. Their flexibility and generative capabilities provide ample opportunity for different knowledge extraction practices, allowing NPD teams to apply one model for a large variety of tasks. Their context awareness plays a critical role in understanding important connections within a given text and extracting relevant information and knowledge. In the following, we provide three specific examples, namely text summarization, sentiment analysis, and customer insight generation, which highlight different knowledge extraction capabilities of one state-of-the-art transformer-based language model. All of which can help to diverge and explore larger problem and solution spaces in the double diamond framework.

### 3.2.1 | Text summarization

Extracting knowledge from text requires the identification, selection, and processing of large amounts of textual data, which can be very costly and time-consuming as well as overwhelming for humans. This might lead to unwanted consequences such as biased decision-making, as humans tend to make simplifying assumptions to be able to process such large volumes of information (Simon, 1955). Transformer-based language models provide an adequate solution to such problems through their ability to summarize text efficiently while conveying the most important aspects and meaning of the original text. They are especially well suited for such tasks as to their context awareness and the ability to pay special attention to the most relevant pieces of information. This gives them a great advantage over earlier text-summarization algorithms, which struggled to understand sentiment and meaning in textual data (Fan et al., 2006). Nonetheless, we also acknowledge that algorithmic approaches to text summarization are not without potential trade-offs, such as questions regarding the trustworthiness of AI-generated summaries. The potentials and limitations of

this technology raise important questions for further research as well as practitioners that we address later in this article.

To showcase the text summarization capabilities of state-of-the-art transformer-based language models, we provided GPT-3 with the text of a blog post reviewing camping gear (in this particular case a portable power station). This serves as an example of a source of potentially valuable information for innovation projects. At the time of writing this article, a Google search for “camping blog” produced 299 million search results, far more than any human could ever read when building background knowledge for, for example, a product development project in this domain. Therefore, having a way of extracting the most relevant information from such articles through AI-generated text summaries can provide an easy solution to identifying the most relevant articles and exploring a larger problem space. Having chosen an exemplary blog post, we first prompted GPT-3 to summarize the text (Prompt A2.1 in Table A2-1 in the web appendix) and then prompted the model to summarize the text in just one sentence (Prompt A2.2) to test an extreme case of automated summarization.<sup>2</sup> This is the summary created of a long blog post by the GPT-3 algorithm (as a response to Prompt A2.1):

The Jackery Explorer 500 is a portable power station that can be charged up in a variety of ways and then used for your off-grid adventures. It has a capacity of 518 Wh (21.6 V, 24 Ah), a cell of Li-ion NMC, and a lifecycle of 500 cycles to 80%+ capacity. It can be recharged in 7.5 h via AC adaptor, 8 h via 12 V car adaptor, or 9.5 h via Jackery Solar panel (sold separately). It has multiple outputs, including AC (230 V, 500 W, 1000 W surge), USB-A (5 V, 2.4A), car (12 V, 10A), and DC (12 V, 7A). It is designed to be used for charging devices such as phones, cameras, laptops and drones, and can also be used for mini-coolers and TVs. It is priced at £529.99 for the power station alone, or £749.99 with the solar panel included.

This and the other examples documented in the web appendix show the general ability of transformer-based language models to capture the essence of an original text

<sup>2</sup>In the web appendix to this article, Table A2-1 provides the input and output for Prompts A2.1 and A2.2. As a further example of GPT-3's knowledge extraction capabilities, we tasked the algorithm to summarize an editorial from JPIM (Spanjol & Noble, 2021). Table A2-2 provides the results. We invite readers to compare these summaries with their own reading of the original text.

and reproduce a coherent, yet substantially summarized version of it. In this way, language models help to speed up knowledge extraction by supporting humans in quickly understanding the essence of a text and identifying relevant text passages faster. Hence, innovation teams can reduce knowledge-extraction efforts and re-distribute their focus to applying the acquired knowledge to their innovation tasks. In addition, transformer-based language models can help overcome problems of myopic search by enabling users to access more data more quickly that might otherwise be outside their area of expertise.

Despite these potential upsides of using such technologies, it should be noted that there currently is no way of telling how reliable an AI-generated response is without knowing the answer to a question oneself. This is somewhat defeating the purpose of using an AI in the first place. Many models are currently able to generate very plausible text passages that sound as though they could be true, but might not necessarily be. Therefore, a weakness of transformer-based language models could be that they do not just retrieve answers to a question from a set of pre-defined responses, but generate an original response from scratch. If provided with the task of generating output, a language model will not tell a user that it does not know the answer (as a human hopefully would do)—it will simply produce the most likely answer. In this sense, transformer-based language models are still a rather narrow form of AI, even if they bring us one-step closer to reaching artificial general intelligence.

Problems of reliability arise specifically in areas where rather limited amounts of relevant knowledge on a subject were included in the initial training data. Innovation generally happens at the frontier of knowledge and oftentimes requires firm-specific knowledge that is not encoded in text corpora used for training of general language models. However, companies can potentially mitigate this problem by re-training or fine-tuning existing models with their firm-specific knowledge. Nonetheless, humans using such technology to innovate need to be aware that such limitations exist and have to use their expertise to screen AI-generated output for such problems. Hence, further research needs to investigate in which contexts and under which conditions transformer-based language models can perform a text summarization in a better way than humans. But rather than a comparison of humans vs. machines, further research should investigate how humans' domain expertise can support language models to utilize their abilities best, for example, by formulating the summarization task in a specific way or pre-selecting the text corpus for analysis.

### 3.2.2 | Sentiment analysis and insight generation

Another task that transformer-based language models are well equipped to handle is to mine the overall sentiment of a given text corpus. Especially online communities contain information that is valuable for innovating firms, as customers discuss products, services, and trends online that have an impact on a firm's product development process (e.g., Blazevic & Lievens, 2008). For instance, customer reviews contain important information on whether customers liked or disliked certain product features or what needs might not have been met. Sentiment analysis is an established methodological approach for analyzing data from social media streams, user forums, or customer reviews (Feldman, 2013). It is valuable as it helps firms to better understand customer needs and can highlight areas where improvements to products and services are needed. As extracting relevant sentiment from large streams of data manually is a laborious task, sentiment analysis has been automatized through ML approaches before. However, similar to text summarization, this required special software and often costly licenses. Broad transformer-based language models like GPT-3 hence promise an opportunity to greatly improve the accessibility and scalability of sentiment analysis.

To explore these abilities, we took a set of 10 customer reviews for an electric portable air pump from [Amazon.com](https://www.amazon.com).<sup>3</sup> We chose five reviews with positive and five with negative sentiment, specifically selecting reviews that varied in length and writing style to provide a realistic real-world sample. Provided with just four examples containing our own (human) assessment of whether the sentiment was overall positive or negative, GPT-3 labeled all of the remaining six customer reviews correctly, showing that it can understand sentiment within text.<sup>4</sup> Again, the model was originally not specifically trained to perform sentiment analysis. While we only provide 10 customer reviews in this example, this approach is highly scalable and can easily be applied to basically infinitely many reviews (or other forms of text) showing how this can help to cover a larger problem space than would be feasible for humans alone.

A typical insight for an innovation project is not just information on whether customers respond positively or negatively to a given product, but rather understanding what customers specifically liked or disliked. Hence, we built on the previous example to test GPT-3's question-

<sup>3</sup>[https://www.amazon.com/-/en/dp/B08SW6WVH3/ref=cm\\_cr\\_arp\\_d\\_product\\_top?ie=UTF8](https://www.amazon.com/-/en/dp/B08SW6WVH3/ref=cm_cr_arp_d_product_top?ie=UTF8)

<sup>4</sup>A detailed overview of the input data, model parameters, and AI-generated output is provided in Table A2-3 of the web appendix.

answering capabilities. Switching tasks mid-prompt, we continued the session outlined before by asking GPT-3 to identify features of the product customers (dis)liked (Prompt A2.7 in Table A2-3 in the web appendix). The model understood that the task had changed and was able to correctly answer which features customers (dis)liked. It also specified in its response why customers (dis)liked these features. This is the output of the model (we present another example and model parameters in Table A2-3 of the web appendix):

The most common feature that customers liked was the built-in light. The light was bright enough to illuminate a tent or a picnic table, and it was a convenient way to light up a dark campsite.

Sentiment: Positive.

This example highlights the flexibility of transformer-based language models. In a way, these models possess the ability to understand customer needs and can extract such knowledge with great accuracy and without extensive training—and at a scale that humans are not able to cope with efficiently (just consider the millions of reviews added to a site like Amazon every single month). Automatically distilling such knowledge to a level where humans can then continue to work with helps innovation teams to concentrate on turning the insights collected during the problem articulation phase into value-creating new products. These opportunities for augmenting human innovation teams raise questions about whether conventional approaches to market intelligence or social media analysis in NPD should still be used, and when.

Further research needs to test and validate these opportunities and potential constraints, also considering how humans and AI interact with and inform each other. Consider our example of providing our human perceptions of “positive” and “negative” in the few-shot learning process above (also see Prompt A2.6 in the web appendix). How dependent is the algorithm's outcome on a human's perception of positive or negative? Does an algorithm perceive, for example, a negative comment still as constructive, providing valuable insights, while a human might have dismissed such a comment as “just another complaint”? This raises many questions about how tasks should be allocated to humans or AI in the innovation process of the future, which antecedents influence this division of labor, and under which circumstances a collaboration of humans and AI provides the best results. We will explore the latter thought of a “hybrid intelligence” (Dellermann et al., 2019) in the discussion section of our article.

### 3.3 | Exploring solution spaces with AI (idea generation)

After exploring problem spaces and extracting relevant pre-knowledge, innovators explore solution spaces and thereby generate new knowledge previously not available to their organization. Such knowledge-based practices are at the core of our understanding of problem-solving and innovation (Crossan et al., 1999). Corresponding processes generally involve innovation teams employing their creativity; a trait that for a long time had been considered inherently human (Boden, 1998). However, there is growing potential in the application of AI to creative tasks (Amabile, 2020). Especially transformer-based language models can be highly relevant in this context due to their ability to generate ideas based on a question or other initial input, as some practitioners such as the design firm IDEO have started to explore (Syverson, 2020). Because of their few-shot learning capabilities, they can generate adequate responses to a given problem statement and come up with original and useful ideas when prompted with just a few examples of what typical brainstorming results look like. In addition, users of such models can precisely tune them to produce more creative (radical) or more deterministic (incremental) responses—an ability rarely imaginable for humans. While we focus on idea generation in this article, transformer-based language models can also generate other text-based output, such as computer code, which plays an important part in many NPD projects today.<sup>5</sup>

An important activity at the front-end of innovation, but also during technical development, is idea generation. It has been shown as being central to a firm's innovative performance (Kijkuit & Ende, 2007). To generate valuable ideas, we employ creativity, generally defined as “the production of novel, useful ideas, or problem solutions” to a given task (Amabile et al., 2005: 368). To explore transformer-based models in idea generation, we first continued the camping gear example from the previous section. We asked GPT-3 to “Create a list of ideas for ways to improve an air pump made for camping.”, and it came up with ideas like adding a carrying handle to the air pump for easy transport or adding an adapter for inflating inflatable camping mattresses (see Table A3-4). Building on one of these ideas, we prompted GPT-3 with a new formulation of the task (“How might we make a portable air pump more useful for campers?”), and now also provided one example idea (to micro-train the model). The algorithm came up with a new set of ideas, which all seem to be reasonable and possible starting

<sup>5</sup>We illustrate GPT-3's code generation capabilities in Appendix A3, Tables A3-5 and A3-6. However, as this is rather a closed engineering task, we do not further discuss this application here.



points for new features in an NPD project (see Table A3-5 in the web appendix). While humans could also have generated these ideas easily, the algorithm produced them within seconds, providing a continuous flow of ideas whenever prompted, but fine-tuning an idea further when prompted to do so. This can largely increase the creative solution space of an NPD team, at almost no cost.

We also explored a more open (fuzzy) question, tasking GPT-3 with exploring opportunities of a new technology. We prompted the AI with two similar, but slightly different questions regarding the use of transformer-based language models for innovation, providing in both cases four ideas generated by us as a starting point of the human-AI interaction (Table A3-1 in the web appendix). The AI-generated ideas contain a few notable characteristics that highlight how language models can prove valuable in an innovation project. On the task “How might we use transformer-based language models in innovation processes,” the algorithm suggested to ...

- Use language models to generate ideas for patent applications.
- Use language models to find similar patents to help in patent searching.
- Use language models to help in monitoring communication between different departments or people.
- Use language models to predict trends in what people search for in the future.
- Use language models to generate possible headlines for news stories.
- Use language models to generate possible names for new products.

Except for the second-last response, which only loosely relates to innovation processes, all responses generated by the AI are relevant in the given context and are viable suggestions. While some answers are more original than others, they build on the four provided examples without just copying them. As the responses are both useful and novel, we can induce that transformer-based language models such as GPT-3 are capable of producing creative output. This is exactly what Amabile (2020: 251) calls AI creativity: “the production of highly novel, yet appropriate, ideas, problem solutions, or other outputs by autonomous machines.”

Another interesting observation in our exploration stems from the comparison of the AI-generated ideas for prompts A3.1 and A3.2 (in Table A3-1 in the web appendix). For both tasks, the examples provided by us to train GPT-3 were the same. We only slightly modified the task (with no changes to the model’s settings), asking for

opportunities “to foster innovation” in the second case. Still, the differences in the results are striking. For the slightly more general prompt A3.1, the model generated ideas related to different stages in an innovation process – from the front-end to the diffusion stage. The response to the more directed prompt A3.2 covered various stakeholders involved in innovation processes, from taking a micro-level focus on team members, an organization-level focus on how firms can use the technology to improve or expand products, to a customer-focused perspective with use cases to make products more useful and fun. Hence, the model seems to be able to take different perspectives. This suggests that GPT-3 implicitly learned during its initial meta-learning process that there are different viewpoints on managing innovation. Remember that we only prompted the model with the word innovation, but did not provide any more explanation or context on what innovation is, how it works, and what is relevant in this context.

These examples show the impact that “prompt engineering” can have on the output of such AI models. Prompt engineering recently evolved as a way humans work with complex AI systems, particularly NLP tools like GPT-3. The more autonomous machines become in providing the desired outcome, the more critical the task that is promoted to the machine producing the outcome. While prompt engineering has been covered in the AI and engineering literature, we still have no knowledge about this new function in innovation management – but perhaps can build on the rich kinds of literature on task and problem formulation in creativity workshops or open innovation contests.

Related to this, we explored how changing model parameters like the temperature setting (see Table A3-2 in the web appendix) can be used to control the scope (openness) of the search space (performing a narrower or broader search). Potentially, this could be used to adapt to changing goals within an ideation session. Given the large body of research on openness of search in innovation management (Salter et al., 2015; Sofka & Grimpe, 2010), this ability could have a large influence on how firms approach open innovation in the future, as it makes it far easier to tap into external knowledge that is encoded in the AI’s knowledge base. Generally, the sheer amount of data used for training purposes of transformer-based language models can provide the basis for a very broad exploration of relevant ideas from various contexts and should be able to support divergent thinking.

However, the examples also highlight that there is still room for improvement. Some of the ideas are not very elaborated. Still, humans in an innovation team can use the ideas generated by the language model and build

on them. They can feedback these results into the model as new examples during further few-shot learning, generating new AI-generated responses by iteratively building upon new knowledge—exactly as humans would do in a brainstorming workshop. But how exactly such hybrid iterations between humans and AI in the innovation process can be facilitated best remains the subject of further research. Especially looking into the organizational antecedents of successful AI-augmented innovation projects could be a promising research avenue. Research could investigate how the implementation and adoption of transformer-based language models are fostered by dedicated structures and processes, including governance decisions like using open source or proprietary language models or how to place the AI capabilities in an innovation team. This also asks for a reconsideration of established frameworks of knowledge absorption and adoption, for example, considering the Not-Invented-Here syndrome (e.g., Antons & Piller, 2015) or different judgments of errors and failures made by humans and algorithms.

An important limitation to consider here is that the original training data for language models has a cut-off point after which new knowledge is no longer contained in the training set used for unsupervised learning. Hence, critical information might not be included in the model's knowledge base. Users have to be conscious of this aspect when interacting with a model. Generally, this natural data cut-off point calls for a continued re-training of models in use. While this aspect might not be critical for applications such as lyric composition or the writing of novels, it is especially relevant in the innovation sphere as innovators should base their decisions on the newest knowledge available. This aspect is even more pronounced in research fields where this knowledge stock expands rapidly. At the same time, the re-training of these models is very easy. These models can very effortlessly acquire new knowledge that can then be incorporated into innovation processes, as long as the information is available in a machine-readable form.

Another important aspect is the quality of the data used for training purposes. Just as with any other type of AI that is based on large amounts of data, language models can potentially suffer from biases. Most models use training data based on text crawled from the internet. Such text generally has not specifically been checked for bias. Developers of models like GPT-3 seem to be aware of this problem and discuss gender, race, and religious biases in their article (Brown et al., 2020). In addition, there are active attempts to increase the quality of the databases used for training. For example, Radford et al. (2019) have created the WebText dataset that only includes text from websites whose outbound links on

Reddit have received at least three karma on the platform.<sup>6</sup> Such measures can ensure a certain degree of data quality.

However, the bias problem is still far from being solved (Heaven, 2020). Therefore, users of language models should always be aware that they could generate biased content. Consequently, employing language models in teams with humans that can check for potential bias appears to be a sensible approach to incorporating such AI in innovation processes—underlying the idea of hybrid intelligence. This also necessitates the active management of such teams, including, for example, the training of employees in searching for and reflecting on biases. Acquiring such skills might then even help humans become more aware of their own biases, allowing humans and AI to learn from each other.

#### 4 | DISCUSSION: THE EMERGENCE OF HYBRID INNOVATION TEAMS

Exploring several use cases, we showed how a specific type of AI, transformer-based language models, can help NPD teams to extract meaningful insights and sentiment from large volumes of text and can contribute to ideation and problem-solving tasks along the entire double diamond model. The ability of transformer-based language models to integrate knowledge from various and diverse knowledge bases allows innovators to increase the quantity, quality, and diversity of ideas and to create more value in their innovation processes—at a very low cost (the price we had to pay OpenAI for executing all tasks explored in this article was less than \$1). Consequently, AI blurs the line between internal and external knowledge and allows innovation teams to tap into a larger pool of knowledge than was previously possible.

In this respect, language models could be seen as a further iteration of the open innovation paradigm. The abilities of language models to interact with different knowledge sources, learn from them, and share and transform knowledge allow this kind of AI to act as a knowledge broker that facilitates sharing of knowledge between different stakeholders, while also fostering the creation of new knowledge (Waardenburg et al., 2021). Thereby, AI can take on some of the functions that were traditionally provided by innovation intermediaries. Through their flexibility and adaptability, enabled by meta-learning during pre-training, innovation teams can employ these language models to access existing

<sup>6</sup>Reddit uses karma as a scoring system to measure how much other users liked posted content.

**TABLE 2** Research themes on transformer-based language models for innovation

Research theme	Level of analysis	Research question
AI capabilities	Technical	<p>What are the differences between problems and solutions identified by an artificial intelligence (AI) and by humans from a given body of text? How and when are humans still superior in reading “between the lines” and making serendipitous discoveries?</p> <p>How do different prompts and task formulations influence the outcome of transformer-based language models? How can we formulate problem statements that are best suited for the usage in AI models for different stages of new product development (NPD)?</p> <p>How and when is AI better equipped to pick up on relevant (“sticky”) information that humans might overlook? Can an AI identify latent need information?</p> <p>(How) can an AI prioritize and select high-quality ideas?</p>
Role of humans/AI in hybrid innovation teams	Team and Individual	<p>Which factors influence how work shall be allocated to humans versus AI models in hybrid innovation teams? What is the right balance between automation and human collaboration?</p> <p>How will the introduction of AI to processes like idea generation change the role of humans in creative tasks?</p> <p>(How) will humans and AI jointly define search spaces? How will humans and AI interact and inform each other?</p> <p>What are drivers of satisfaction when NPD teams augment their work with AI?</p> <p>Will the interaction among humans change when an AI becomes part of an innovation team?</p>
Structures, processes, and governance	Team  Process  Meta	<p>How can a hybrid interaction between humans and AI in innovation processes best be facilitated? What is the role of management in hybrid innovation teams? Can an AI become the project manager in an NPD project?</p> <p>How can the opportunities of joint ideation between humans and AI be captured best to maximize value creation?</p> <p>How should the implementation of transformer-based language models into problem and solution exploration be organized on the project level?</p> <p>What is the impact of AI on established process models for NPD like agile development, design thinking processes, or stage-gate?</p> <p>How should the implementation and adoption of transformer-based language be governed? Who is the process owner of an AI-augmented innovation process?</p> <p>Which IP protects the output of transformer language models? Who becomes the inventor in hybrid innovation teams? What are the consequences of hybrid innovation on different institutions of value capture?</p>
Unintended consequences	Meta  Team  Individual	<p>What are counterproductive effects or unintended consequences of the introduction of transformer-based language models into existing innovation practices?</p> <p>How can innovators deal with (unobvious) biases in AI-generated content?</p> <p>Will inventors lose their creative skills when an AI model is included in idea generation (similar to humans using their navigation skills when relying on GPS systems)?</p>
Trust into AI	Individual meta	<p>What are implications for established frameworks of knowledge absorption and adoption, for example, different judgments of errors and failures made by humans and algorithms?</p> <p>How and when will humans trust computer-generated summaries or AI-generated solutions to capture all the relevant information? Will there be a new kind of “Not-Invented-Here” problem?</p> <p>How and under which circumstances are humans willing to rely on AI-extracted information for their innovation projects?</p>

TABLE 2 (Continued)

Research theme	Level of analysis	Research question
Market dynamics	Meta	<p>As the development of proprietary transformer-based language models is very cost-intensive, will the R&amp;D function move to a few big tech firms offering “innovation as a service”?</p> <p>What are the effects on competition when all firms in an industry rely on the same innovation algorithms provided by a small set of specialized service providers (like OpenAI)? How can AI become a driver of differentiation?</p> <p>What are the ecological (energy) costs of adding transformer-based language models to the innovation process: Is hybrid intelligence sustainable?</p>

knowledge outside a firm. Models that have been trained on large text corpora from the internet have knowledge on a wide range of topics, which opens up the opportunity for innovation teams to integrate knowledge that might lay outside their area of expertise. Given a prompt by a human, AI can help to establish connections between concepts and ideas that might otherwise not have been obvious to humans alone. Few-shot learning capabilities then allow for easier interaction between an innovation team and the AI. The team members only have to provide a limited amount of exemplary responses to a given task, so that the language model can generate adequate output. A human actor can then build upon this output. By providing the language model with their own knowledge and ideas through natural language, innovation teams can integrate the AI into their existing processes, as if it would be a new colleague. The combination of knowledge from human team members and knowledge provided by AI provides the opportunity to greatly improve the productivity of NPD practices and to produce outcomes that would not have been possible with just the skillset of one of the actors.

Our exploration not only demonstrated the capabilities of these algorithms, but also identified many opportunities for future research focusing on particular abilities and applications of AI models for the various stages of the innovation process, like opportunity recognition (e.g., identifying trends and customer needs, predicting technology trends, or providing technology forecasts), ideation and concept development, concept selection (e.g., selection algorithms overcoming human decision biases), design and development (e.g., generative design algorithms to create technical designs, prototypes, and solutions), and launch and lifecycle management (e.g., approaches to mine large pools of information on product performance or customer satisfaction). Considering the fast-paced development of AI, we expect even more powerful models soon.

Still, it is unlikely that these models will be working autonomously, that is, that new products can be

developed entirely by a set of algorithms interacting with each other, with humans just providing the initial prompt. Our exploration of the GPT-3 algorithm for various use cases suggests that we consider algorithms rather as members of an innovation team. Hence, we propose that transformer-based language models will specifically support knowledge-based innovation practices in the form of hybrid intelligence, that is, the combination of human and artificial intelligence, “thereby reaching superior results to those each of them could have accomplished separately, and continuously improve by learning from each other” (Dellermann et al., 2019: 640). Hybrid intelligence aims to combine the best of both worlds (Piller et al., 2022). Some tasks in the innovation process can be probably automated by an algorithm more reliable and cost-effective than they can be conducted by humans. An example is the continuous scanning of social media posts to derive latent customer needs (opportunities) in the front-end of NPD. However, humans still have unique capabilities. Consider situations that need empathy, creativity, or ethics (van der Aalst, 2021). Decisions here demand human contributions and cannot entirely be executed by a machine. AI and human intelligence will complement each other.

Hence, building and orchestrating such hybrid teams and allocating tasks between humans and machines becomes a new management task for project leaders. Understanding the contingencies and success factors of these allocation decisions is a domain with a wide demand for further research. Managers will have to take into consideration the distinct characteristics of human and non-human actors and their collaborations. While humans will play a major role in providing context, steering language models toward desired results, and embedding AI output in the larger innovation picture, transformer-based language models can speed up many tasks that require the handling of large amounts of text, understand patterns in data invisible to humans, and make connections between knowledge bases that might not be readily available to human team

**TABLE 3** Research questions generated by GPT-3  
(classification added by authors)

Research theme	Level of analysis	Research questions
Managing innovation	Organizational	What are the best ways to manage and monitor AI-based innovation processes?
	Process	How does the increasing use of AI in innovation processes change the way we think about innovation?
Effects on society and the economy	Meta	What are the best ways to measure the impact of AI on innovation processes?
		What policies or ethical considerations need to be in place to ensure that AI-based innovation processes are responsible and beneficial to society?
		What are the possible long-term effects of AI-based innovation processes on society and the economy?
		What are the potential risks and benefits of AI-based innovation?
		How can we ensure that AI-based innovation is responsible and beneficial to society?

Abbreviations: AI, artificial intelligence; GPT-3, Generative Pre-trained Transformer 3.

members (Piller et al., 2022). At the same time, including algorithms as team members may also change the way how humans interact with each other in a team. In the concluding section of our article, we will discuss some of the related research questions in more detail.

## 5 | CONCLUSION AND OPEN RESEARCH QUESTIONS

Transformer-based language models are a powerful form of AI that can augment human innovation teams and hold the potential to fundamentally change how knowledge-based practices will be approached in the future, thereby

improving innovation performance. Their ability of understanding, generating, and adapting language, fostered by meta- and few-shot learning and attention mechanisms, make these AI models a powerful tool in any innovator's toolkit, enabling innovation teams to explore larger problem and solutions spaces. However, transformer-based language models are not without limitations. We discussed their most important constraints throughout this Catalyst but want to emphasize that these limitations do not render transformer-based language models useless, but rather highlight that such technology should not be trusted and used blindly. Given the speed of development in this field, we are optimistic that future generations of language models will mitigate at least some of the limitations of current state-of-the-art models.

Comparing their skills and limitations, we consider transformer-based language models not as a stand-alone technology, but rather as an actor in an innovation team that needs to be integrated into existing processes in the understanding of hybrid intelligence. At present, we are far from understanding all the potential use cases, benefits, and pitfalls associated with such hybrid innovation teams. More research is needed, not only from a technical but particularly also from a managerial perspective. We encourage scholars to take our work as inspiration to dive deeper into the possibilities and implications for innovation management associated with transformer-based language models. Hence, we conclude this Catalyst with two sets of research questions. Table 2 contains those questions we find especially relevant, considering our own practical experience of working with GPT-3 and reflecting on the results. This list is by no means exhaustive but can provide a starting point to explore the various aspects that transformer-based language models may affect, including units of analysis on the technical, individual, team, organizational, and industry (meta) level. In addition, building on the idea of this article, we also prompted the GPT-3 algorithm to continue our list of research questions presented in Table 2. Table 3 provides its output. We hope that both sets of questions inspire other scholars to investigate transformer-based language models and their implications for NPD and spark a fruitful discussion on the collaboration of humans and AI for innovation.

Answering such research questions requires scholars to apply a multitude of research methods and interdisciplinary research. We still lack dedicated theories that can explain and design collaborative ideation and problem-solving by humans and AI. Hence, answering these questions will often best be achieved through inductive and abductive, rather than deductive reasoning (Amabile, 2020; Bamberger, 2018; von Krogh, 2018). Following a grounded theory approach and building on a multitude of research methods is likely to yield the best results.

First, observing ensembles of humans and AI in a real-world context could lead to valuable insights into possible tensions arising in such collaborative environments. One example that lends itself well to such an approach is the use of generative design software by NPD teams. A similar approach has been successfully applied to studying the introduction of a predecessor of generative design software, namely early CAD software, into NPD processes (Thomke, 1998). Accordingly, such an approach would mostly rely on observations, interviews, and supplemental material provided by industry experts. Then, building on initial insights from such studies warrants the use of dedicated experiments to afford researchers more control over specifics of human-AI collaboration in innovation and allows for more targeted hypothesis-testing derived from observations made in a real-world context. Such experiments could, for example, test the performance effects of different constellations of hybrid intelligence, but also explore how prompt engineering would influence the outcomes or the acceptance of contributions by an AI to an NPD project.

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The authors have read and agreed to the Committee on Publication Ethics (COPE) international standards for authors.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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