Is Artificial Intelligence a Better Researcher than Humans?

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Abstract: In the last few years Generative Artificial Intelligence (GenAI) has taken universities by storm. This does not only affect the way what and how to teach and how to assess knowledge and competences in exams, but it also impacts the way how to do research. On one hand, GenAI has fast access to a huge amount of wide-ranging (explicit) knowledge and the capability to extract and combine knowledge that seems to be relevant in the context of certain research. On the other hand, research is closely linked to the human capability of being creative showing curiosity, care, collaboration, and critical thinking. Against this background, the paper addresses a question of immense social and also ethical relevance: May we use (Gen)AI as tool for scientific research and if so to what extent? The paper starts analysing the problem from a theoretical and conceptual point of view by comparing capabilities of GenAI with those of a good researcher. Based on this the complete research cycle is investigated to understand which capabilities are more helpful to achieve research results of high quality and novelty, but in an effective way. To gather empirical data from a self-experiment, the setup of an unexperienced researcher (e.g. PhD student) with just a rough idea about the intentional research focus was chosen. Addressing the first and fundamental phase of any research process, idea generation, by comparing performance of an AI researcher with a human one, results demonstrate the usefulness of combining strength of both worlds mandatorily keeping the human researcher in the loop. With this, the paper focusses on chances and challenges coming with the highly dynamic evolution of AI within a complex, knowledge-intense application area where human experience, problem-solving capability and creativity is decisive. It contributes to discussions about necessary adjustments in how organizations (and particularly universities) manage their knowledge generating potential considering artificial and human intelligence.

Keywords: Generative artificial intelligence, Knowledge, Research quality, Research efficiency, Human-in-the-loop

1. Introduction

Artificial Intelligence (AI) is one of the most promising technological advancements, but also one of the most ambivalently discussed topics these days. The latter starts with its definition already, as there are two different perspectives, a psychological and a computational one. Gignac and Szodorai (2024) elaborated operational definitions of both artificial intelligence and human intelligence (HI). They differentiate AI from HI just by referencing to an artificial system and computational algorithm instead of a person and his/her perceptual-cognitive processes for completing a novel standardized task. The latter is a task (or test) with limited chances for preparation, as it neither was introduced before nor awareness was risen that this type of questions should be solved. This is typically the case when it comes to answering a research question. As this is a particularly challenging task to human researchers, might they be young ones (newcomers, typically PhD students) or experienced ones (researchers well recognized in a certain community), any kind of approach, method, methodology, source of inspiration, or even tool is welcome to provide support.

With the advent of generative Artificial Intelligence (GenAI), it suddenly seemed to be easy to speed up research. GenAI refers to integrating machine-learning models to fabricate novel content based on large datasets that train the generative model (Dwivedi et al, 2023). To understand the power of this not so new, but suddenly widely available tool, AI is benchmarked by putting its performance in competition to HI performance when dealing with the same tasks. The AI index report 2025 (Maslej et al, 2025) uses different benchmarks to monitor technical progress of AI systems over time. Results show that AI systems continuously improve exceeding human performance at many previously challenging tasks already (see Figure 1).

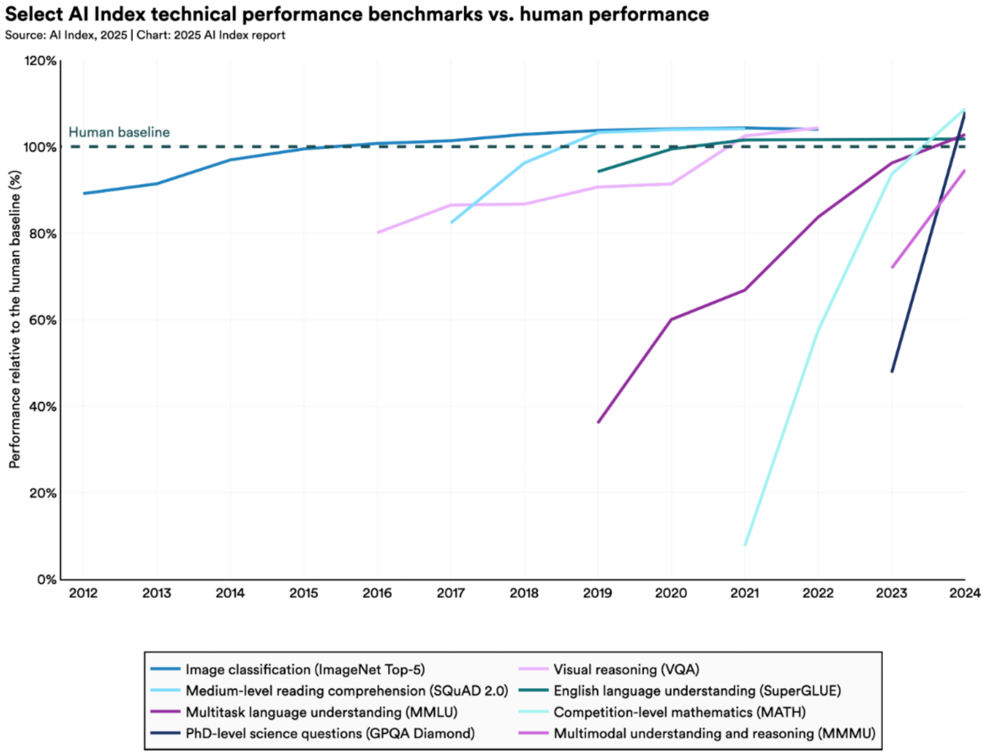

Figure 1: State of AI performance (Maslej et al, 2025, p. 94)

These new opportunities felt particularly welcome as *"… researchers are under extreme pressure to publish high-quality research"* (Lindgreen et al, 2021, p. A13). Consequently, the interest in applying AI techniques and technology in research has been increasing from a growing number of disciplines (Madanchian and Taherdoost, 2025); research employing GenAI is anticipated to accelerate and transform scientific knowledge (Benbya et al, 2024). There are various studies investigating GenAI use in research. They mainly focus on the impact of AI-based or AI-supported research on its productivity (i.e. research efficiency – see e.g. Madanchian and Taherdoost, 2025) or quality (i.e. research integrity – see Andersen et al, 2025, for example) and how to assess them. Those studies are based on literature review or surveys in the field and reflect the situation in that particular moment. Because of the ongoing rapid development and highly dynamic evolution of GenAI, including the immensely growing knowledge base underlying Large Language Models are trained with, on one hand, but also due the raising awareness of researchers of ethics challenges, bias, or risk of failure on the other, there is no comprehensive picture on the extent to what GenAI might be beneficial alongside the research cycle, yet.

Against this background, the paper analyses the potential of GenAI application in a certain research context throughout the entire research process. Are we on the way towards fully automated research solely run by GenAI or will there still be the need for human intervention, i.e. for human researchers? When answering this question, the future need for human capabilities is in focus. The following sections will analyse both, capabilities of GenAI (Section 2) and capabilities of (good) researchers (Section 3). Findings from both sections are brought together and applied to a specific case with regard to the kind of researcher and the chosen research problem to specify what in the research process could or should be taken over by GenAI and what could or should remain in hands of the human researcher (Section 4). Section 5 summarizes discussions and draws conclusions on both, the use of GenAI and the future role of human experts in scientific research.

2. Capabilities of Generative Artificial Intelligence

In recent years, *Generative AI (genAI)* and open access AI tools like ChatGPT, Gemini, DeepSeek, or CoPilot provided a more common user interface moving the use of AI from an expert's competence to an almost everyday tool. Schneider (2025) characterizes GenAI as an AI system based on a foundation model that generates and transforms content based on specific user interactions. In other words, GenAI can generate new data similar to the training data it has seen. Generative models learn the underlying probability distribution of the (enormous amount of) training data and can then generate new samples from this learned distribution (Baum, 2024). *Large Language Models (LLMs)* are specific applications of GenAI designed to understand human language and to generate intelligent, creative responses similar to human-produced content when queried. Because of the ability of processing natural language, AI is capable already to assist humans in many different ways:

- AI-powered *translation systems* use artificial neural networks to translate texts in various languages at high quality of language.
- GenAI tools create *new content* as text, image or video usually in response to human prompts.
- AI chatbots simulate *human-like conversation* through text or speech interfaces to help in customer service, manage appointments, or support travellers in booking trips.

Bots are the simplest form of AI assistance. These automated systems are typically rule-based and designed to carry out predefined tasks without human intervention. Bots can manage repetitive tasks, answer basic questions, and execute straightforward functions. They follow scripts and rely on if-then-else logic, meaning their responses are limited to the scenarios they have been programmed to handle (Alosious, 2024). The integration of LLMs with retrieval mechanisms enhances their response generation to answer precise questions from large databases or address customer queries using information from different company documents. This *Retrieval Augmented Generation (RAG)* is another increasingly common capability of AI combining the strengths of information retrieval and GenAI (Maslej et al, 2025): The model first retrieves relevant information from databases, files or documents and then combines them to generate a response tailored to the user's query based on retrieved content. Because of using those (relevant) external sources instead of training data purely, responses are more accurate and up-to-date.

Co-pilots represent a collaborative approach between AI and humans. Acting as assistants, they provide real-time, contextually aware support, allowing users to complete complex tasks more efficiently. Co-pilots excel in roles requiring decision support and act as an "extra set of hands" that brings data-driven insights and recommendations directly into workflows. This way, they enhance human judgment enabling more nuanced and strategic decision-making (Alosious, 2024).

The latest boost of development moved AI application from those sophisticated communicators or task-oriented AI to agentic AI allowing for autonomous, goal-driven decision-making. With this, AI evolved from prompt-driven content generation (GenAI) via tool-based task execution (AI agents) towards orchestration of full-fledged workflows (agentic AI). *Agentic AI* enables autonomous decision-making, automates processes, and enhances efficiency though transition from assisted (co-pilot) to autonomous (autopilot) models (Hosseini and Seilani, 2025). Agentic AI (or multi-agent) systems composed of multiple, specialized agents that coordinate, communicate, and dynamically allocate sub-tasks within a broader workflow to achieve a common goal are comparable to human experts working in teams. Those agents, i.e. more advanced AI applications with a degree of autonomy and cognitive capability beyond that of a bot, can interpret data, learn from interactions, and make independent decisions within set parameters. They are crucial for tasks that require context-awareness, data analysis, and ongoing adaptability (Alosious, 2024). This constitutes a paradigm shift in AI enabling to act independently, pursue broad objectives rather than isolated decisions, and carry out complex tasks that require reasoning elements such as planning and reflection (Sapkota et al, 2025; Schneider, 2025).

An IBM Think Circle (IBM, 2025) identified a number of use cases despite implementation challenges:

- *Document retrieval and analysis*: Intelligent agents search unstructured data in documents such as product documents, sales documents, contracts and identify what is the best document to choose.
- *Complex data querying*: Code models are used to create SQL queries.
- *Proactive outlier detection*: Intelligent agents look at sets of data, scan them, run and find outliers overnight. They send back results as a morning briefing.

These examples and first use cases underline the potential proper AI integration might have.

These different kinds of GenAI techniques do not only form levels of evolution, but provide a set of tools to support human knowledge processes. They offer different capabilities (and come with different levels of complexity) we can (and should) choose from according to what might be most appropriate and beneficial in a certain application context as, for example, scientific research. To provide a basis for selection the following section analyses what capabilities are required (by a human researcher so far) throughout the research process.

3. Capabilities of a Good Researcher

In order to identify capabilities a researcher (and particularly a good one) should possess, it is helpful to start from identifying the steps and phases of any research process. Literature contains various models for how to conduct research within different contexts and for different purposes. Zapata and Velásquez (2008), for example, present a *conceptual model for writing a research article*. It shows main elements of a research article (i.e. problem, objectives, solution, and future work) and how they are related to each other in order to assure consistent structure and flow in writing. This way the model also indicates elements of the research process the article is based upon. However, to derive what is required from a researcher this model is too generic. Other authors focus more on how to actually research. Alphonse (2023) derives eight *main stages of the research process* from a literature review and puts them in a cyclical process from identifying a research question to presenting findings which might trigger new or further research questions. This proposal considers research as a complex and challenging process which cannot be performed in vague, unprepared, and surprising way. Instead, a researcher needs to define and structure the process to follow well; s/he must be capable to work in a systematic and organized way according to prior planning. Saunders et al (2023) explain the *research process in the field of business* discussing 13 steps in detail from generating a research idea and developing a research proposal to writing and presenting the research report. They particularly point on the necessity to follow a systematic approach moving forward step-by-step instead of jumping in and out or over as it might feel good. Depending on the initial research problem it might also be quite helpful to substructure a complex problem into smaller less complex or more focussed ones. The more a researcher is capable in doing so, the better researcher s/he will be.

Andersen et al (2025) base their survey on GenAI use cases in research at Danish universities on *five phases of a research process* from idea generation to writing and reporting research results. When analysing survey results, they identified *three clusters of GenAI use* in Danish academia that were assessed also as good research practices:

- "GenAI as a work horse" – using GenAI
- *to create and edit software codes for analysis and simulation*
- *to support statistical analysis*
- *to help recognize patterns in data*
- "GenAI as language assistant only" – using GenAI
- *to edit language, e.g. of research proposals*
- *to transcribe recordings of research material*
- *to propose titles, keywords, or abstracts*
- *to edit research articles for readability and formatting references*
- "GenAI as a research accelerator" – using GenAI in almost all use cases, particularly for data analysis and research design, except the creation of synthetic datasets and identifying ethical issues in research.

These clusters of GenAI use show that researchers mainly see benefits for activities that are somehow formal, analytical and repetitive requiring a certain level of accuracy and preciseness from the researcher. On the other hand, activities that require more creative thinking or moral assessment should remain in human responsibility. In terms of research fields, authors saw a closer relation of researchers from technical sciences, especially those ones from experimental technical sciences, and researchers from quantitative social sciences to GenAI usage than of researcher from other domains with more qualitative research. This finding to some extent confirms a general expectation that researchers used to work with software to plan, gather, analyse and interpret data have a lower barrier to give technological advancements a chance and to imagine that and how they might be beneficial in their research. This does not differentiate per se a good researcher from a normal or even bad one, but this capability of being open-minded to new tools that might be supportive in research processes is certainly an advantage "in the race" for higher research productivity and efficiency. Concerning academic age, Andersen et al (2025) observed that more junior scholars used GenAI for more different purposes and much quicker than senior scholars. This demographic influence might result from either digital nativeness of the younger generation or higher level of scepticism of experienced researchers or from both.

The final activity in any research process usually is related to *writing and presenting research results*. As this is the moment when a researcher shares own work with others triggering explicit or implicit evaluation of both, the research conducted and the researcher him/herself, the capability to write a good scientific paper is another requirement when aiming to be a good researcher. According to Dharmayanti et al (2024), good scientific writing depends on digital literacy skills, the capability of critical thinking and to find information online, but also some online writing attitude. Valenti (2014) defines twenty rules to follow when writing a paper. These rules refer to the use of (English) language and text design. On the other hand, papers submitted for publication are typically rejected when they lack sufficient novelty, show flaws in methods or data interpretation, analyse data inadequately, or suffer from poor critical scientific thinking (Setter et al, 2020).

Table 1 relates capabilities of a good researcher as discussed before to phases and activities in the research process as they were derived from literature. This framework will be used in the following section to identify where (Gen)AI outperforms the human researcher already and where the human researcher still is or might be in future the key player in scientific research.

Table 1: Requirements of a (good) researcher in the phases of a research process

	Research phase	Research activity	Capability requirements
1	Idea generation[1,2]	Generating/refining research ideas[2] Identifying gaps in current research[1,4] Identifying relevant literature[1], planning and conducting literature research[2] Summarizing or analysing existing literature[1,2,3,4] Developing an overarching research question[2,4] Writing research aim and set of research objectives[2,4]	• apply creative thinking • find information online • apply critical thinking
2	Research design[1,2,4]	Choosing research methodology[1,2] Developing a coherent research strategy[2] Developing theoretical models or conceptual frameworks[1] Designing experiments[1,3] Formulating research design[4] Assessing the quality of research design[2]	• define and structure research process following a systematic approach • eventually substructure a complex problem • apply critical thinking
3	Data collection[1,4]	Choosing methodology for data collection (experiment, observation, survey, interview)[4] Preparing data collection[4], selecting samples[2] Obtaining and evaluating secondary data[2] Collecting[2], recording, transcribing[1] primary data Generating synthetic data sets[1] Identifying ethical issues in research[1]	• apply creative thinking • assess morally • be open-minded to new tools
4	Data analysis[1,3,4]	Choosing methodology for data analysis Creating or editing statistics, simulation or other software code for data analysis[1,3] Preparing data for analysis Analysing data qualitatively[2,4] (incl. pattern recognition[1]) Analysing data quantitatively[2,3,4] (incl. pattern recognition[1]) Creating or modifying scientific figures or images[1,3]	• work accurately and precisely • be open-minded to new tools • apply critical thinking
5	Writing and reporting[1,2,4]	Suggesting a structure for a research article[1] or project report[2,4] Proposing title, abstract, keywords[1] Drafting[1] and editing article or report[4] Improving readability, language, or formatting[1] Creating a slide deck for presentation[1] Creating non-academic writing for public engagement[1]	• work accurately and precisely • write good scientific papers • show digital literacy skills • use language skills • design text

[1] Andersen et al (2025); [2] Saunders et al (2023); [3] Madanchian and Taherdoost (2025); [4] Alphonse (2023)

4. GenAI Versus Humans in Research Idea Generation

4.1 Methodology

In order to compare GenAI with humans as a researcher it is necessary to define a setting that could be applied to both scenarios. Following findings by Andersen et al (2025) according to which academically younger researchers are closer to GenAI usage than academically older ones (see Section 3), we assumed a fresh PhD student without prior practical or research experience who is looking for a suitable research topic within his/her favourite field of research. With this, focus was put on the first phase of any research process, idea generation, exclusively and, within it, mainly on activities 1.a to 1.d (see Table 1). The chosen field of research matches the authors' core area expertise, logistics, to be able to assess any results with regard to correctness and relevance.

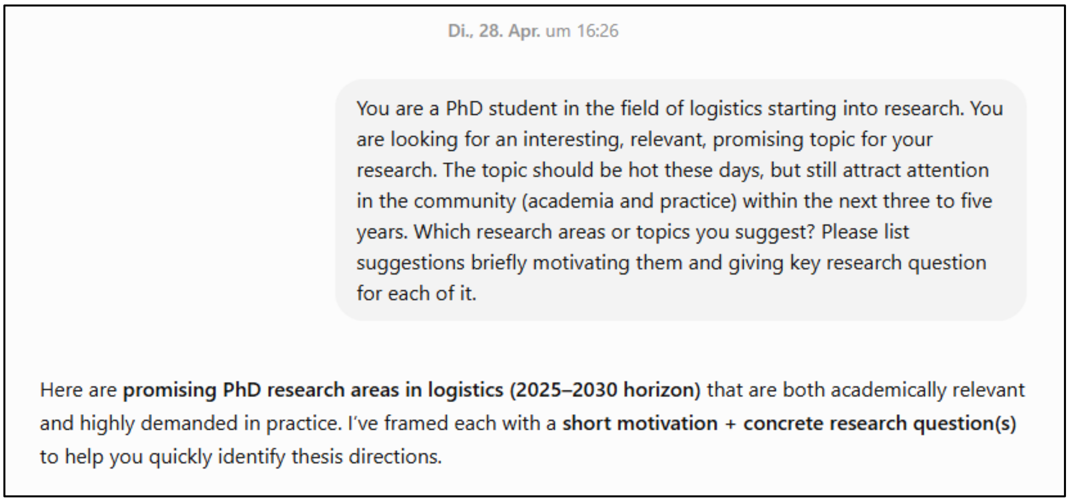

Figure 2: Prompt to and introductory part of response by ChatGPT (OpenAI, GPT-5.5) on research idea

ChatGPT (OpenAI, GPT-5.5) was first asked to propose appropriate research ideas (see Figure 2). In response we got a list of ten suggestions which all met expectations with regard to what is relevant research these days. Each suggested topic was accompanied by motivation ("Why it's hot"), research gap and potential research questions. To support in deciding amongst them the answer also provided recommendations for what should or could be considered and offered help in narrowing down to a concrete PhD proposal (see Figure 3).

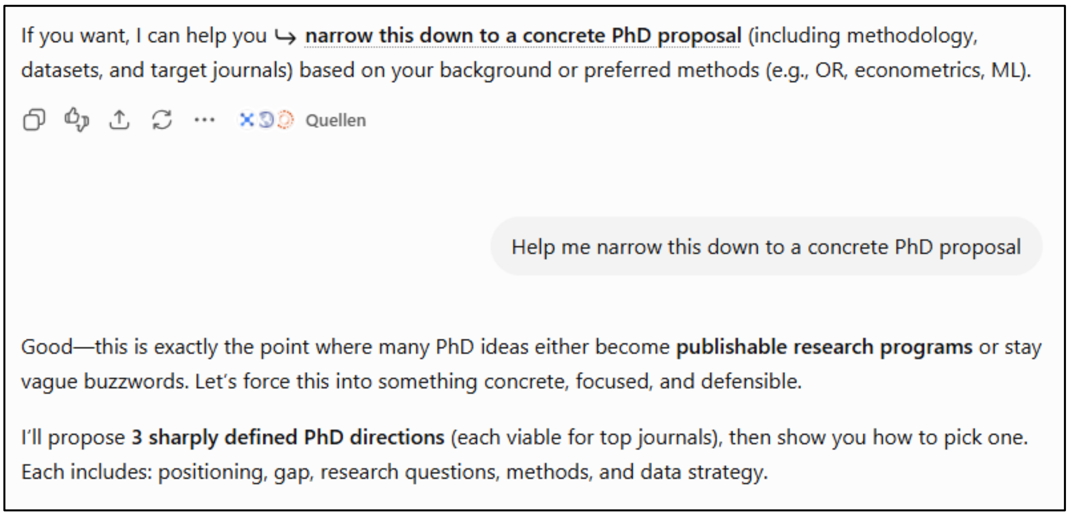

Figure 3: Snippet of the conversion with ChatGPT (OpenAI, GPT-5.5) in response to the initial prompt

The resulting list of three possible directions for a PhD clearly specified and motivated each of them. The chatbot added criteria for how to decide amongst them, provided an *"honest recommendation"* and proposed a dissertation title: *"Human-AI Decision-Making in Sustainable Logistics: Impacts on Cost, Service, and Emissions"*. Conversation went on to finetune the research topic more towards personal fields of interest (see Figure 4).

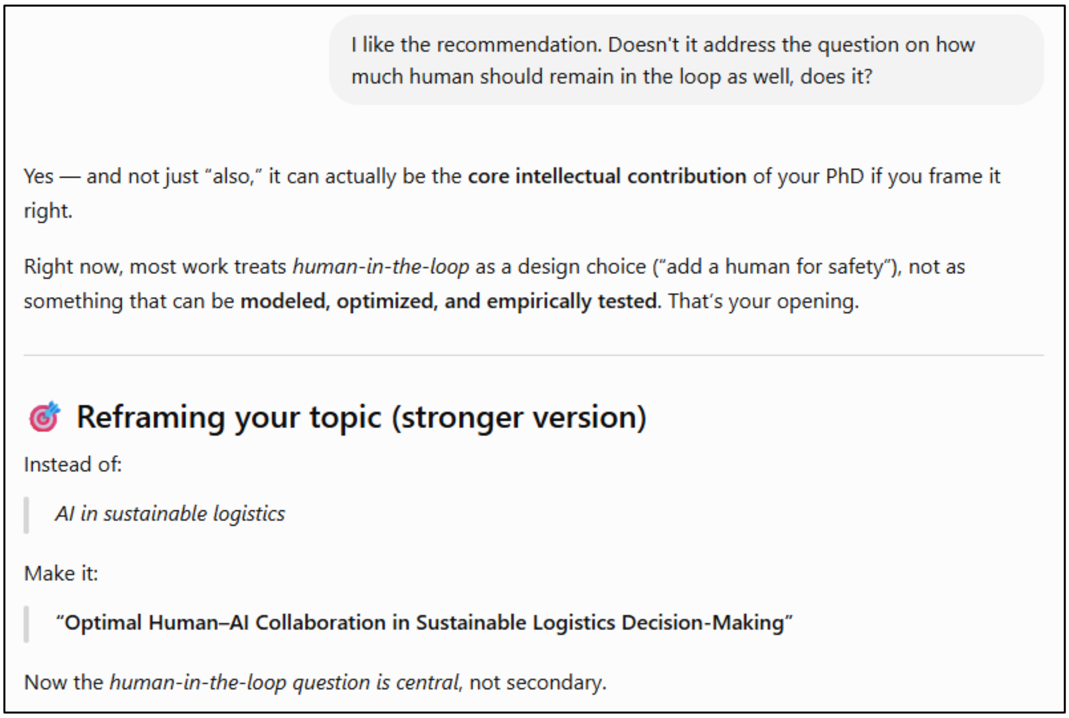

Figure 4: Snippet of the conversion with ChatGPT (OpenAI, GPT-5.5) to finetune research topic proposal

In the end, conversation resulted in *"Optimal Human–AI Collaboration in Sustainable Logistics Decision-Making"* as idea for PhD research (activity 1.a from Table 1) which addresses a highly relevant topic and assumingly meets interest of the PhD researcher. This topic formed the starting point for a comparative analysis of ChatGPT-based and human-driven literature review with the human researcher using SCOPUS as database. Both approaches shared the same goal, to identify state-of-the-art and research gaps related to the chosen topic (activities 1.b to 1.d from Table 1). In order to limit references to a reasonable number within this paper, we first asked ChatGPT to provide the top ten relevant research papers on our topic (see Figure 5). Next, we checked those references for existence, correctness, and relevance in SCOPUS.

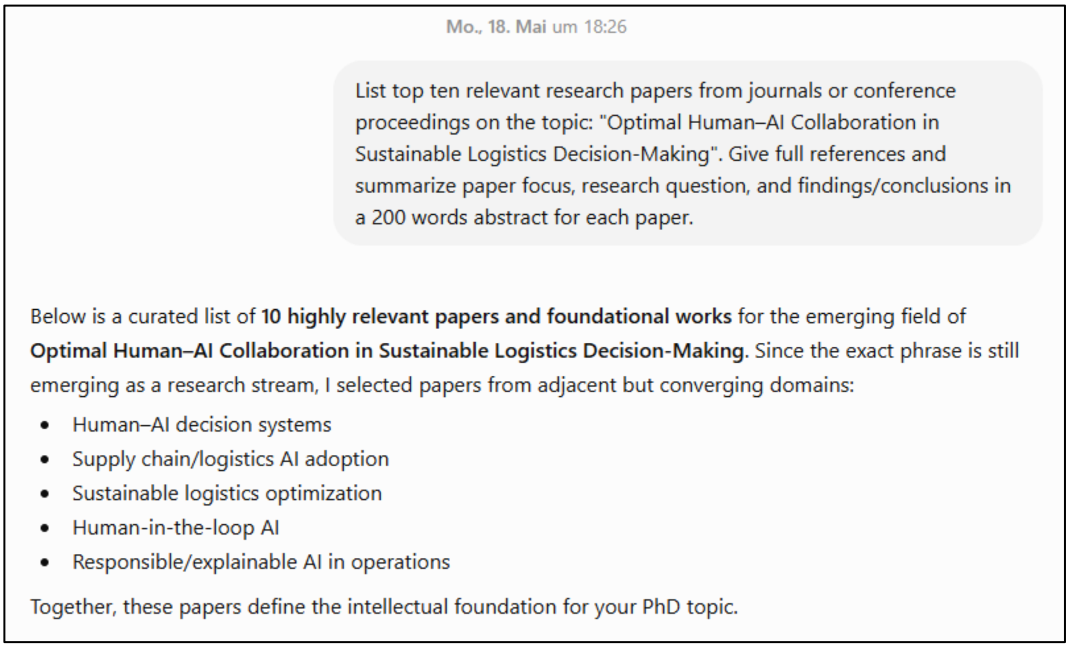

Figure 5: Prompt to and introductory part of response by ChatGPT (OpenAI, GPT-5.5) on relevant literature

4.2 Results

As result from asking ChatGPT for the top ten research papers published in journals or conference proceedings which are relevant for the chosen research topic, ChatGPT elaborated what could be relevant according to own criteria (see Figure 5). As presented in Table 2, a cross-check in SCOPUS of all papers on the ChatGPT list showed interesting findings: 4 out of 10 papers were not found in SCOPUS, 2 more were found with another name. The papers had 343 citations in total with one paper having accounted for more than 60% of those citations.

Table 2: Top ten relevant literature provided by ChatGPT (OpenAI, GPT-5.5); for prompt see Figure 5

Rank	Relevant research paper	Result from check in SCOPUS
1	Yaroson, E.V.; Abadie, A.; Roux, M. (2025). https://doi.org/10.1007/s10479-025-06534-7	32 citations
2	Elgeddawy, Y.G.A. (2026). https://doi.org/10.32628/IJSRSET261316	not found
3	Lai, V.; Chen, C.; Liao, V.; Smith-Renner, A.; Tan, C. (2021). https://doi.org/10.48550/arXiv.2112.11471	not found (2023 remake has 160 citations)
4	Schemmer, M.; Bartos, A.; Spitzer, P.; Hemmer, P.; Kühl, N.; Liebschner, J.; Satzger, G. (2023). https://doi.org/10.48550/arXiv.2310.02108	16 citations
5	Leitão, D.; Saleiro, P.; Figueiredo, M.A.T.; Bizarro, P. (2022). https://doi.org/10.48550/arXiv:2206.13202	not found (same authors have similar studies there)
6	Tsolakis, N.; Keramydas, C.; Toka, A.; Aidonis, D.; Iakovou, E. (2019). *Journal of Cleaner Production*, 222, 281–299.	213 citations
7	Tan, L.; Spiliotopoulou, E.; van Jaarsveld, W. (2025). https://doi.org/10.2139/ssrn.5404170	not found (same authors are quite present there)
8	Qu, C.; Kim, E. (2024). *Sustainability*, 16(14), 6186.	47 citations
9	Zejjari, I.; Benhayoun, I. (2024). *Discover Sustainability*, 5, 174.	29 citations
10	Bahroun, Z.; Saihi, A.; As'ad, R.; Tanash, M. (2026). https://doi.org/10.1016/j.sca.2025.100188	6 citations

To see whether these papers are really the top ten most relevant ones for our research, SCOPUS should find papers matching all key terms of the topic, i.e. “optimal”, “human-AI collaboration”, “sustainable”, “logistics”, “decision-making”. In order to narrow down the total number of 70 papers received to a feasible number, the ten mostly quoted papers should be listed (see Table 3). Amongst them, there is only one paper appearing in both lists: the top ranked paper from the ChatGPT list is the fourth in the SCOPUS list. Therefore, SCOPUS disagrees almost completely with ChatGPT on what are the most relevant sources for research. Papers on the SCOPUS list have a total of 307 citations which is slightly less than the total number of citations found for the ChatGPT list. However, each paper listed by SCOPUS has at least 14 citations, a situation that only occurred with 5 of the 10 papers selected by ChatGPT. From this, we may conclude that if we choose citations (i.e. to what extent the research community works with papers) as an indicator of paper quality, SCOPUS gives on average more balanced results than ChatGPT. ChatGPT is in relation to citations much more uneven; this may be seen as an indication of lower quality of research.

On the other hand, the paper with the far most citations on the ChatGPT list does not appear at all on the SCOPUS list, whereas several references proposed by SCOPUS do not show a direct link to the intended field of research. This might point on a drawback of the SCOPUS search algorithm which is term-based and not content-based. Here, a (Gen)AI tool might provide a cleverer view on the relevant body of knowledge.

This seems to be confirmed by results from narrowing down the initial SCOPUS result asking for the ten most relevant papers. It must be noted that for the SCOPUS search engine “relevance” is a proxy of “similarity”. Therefore, the papers appearing on the third list (see Table 4) are those ones within the group of 70 that are expected to fit more in terms of content as described by the search words given above.

At first glance, we see three papers on this list which already appeared in the previous one (see Table 3), namely papers on ranks 6, 8 and 9. These papers obviously fulfil both criteria of the SCOPUS search, belonging to mostly quoted and most relevant ones. In fact, these papers show a much more direct link to the intended field of research than several of the others even appearing as being off-topic. Again, this indicates the already addressed gap in the SCOPUS search algorithm in going beyond terms and being able to truly understand contents. However, and quite interestingly, this third list includes nine papers published in 2025 or 2026, and therefore the number of current citations is much lower than those of the other two lists – only 121 in total corresponding to barely 1/3 of the number of citations before. The recent publication date of these relevant papers also confirms that the topic suggested by ChatGPT is extremely up-to-date, and that the theory, if it exists already, is being developed by the hour.

Table 3: Ten mostly quoted papers in the field provided by SCOPUS

Rank	Relevant research paper	Indicator
1	Loske, D.; Klumpp, M. (2021). https://doi.org/10.1016/j.ijpe.2021.108236	54 citations
2	Liu, Q.; Ma, Y.; Chen, L.; Skibniewski, M.J.; Chen, Z.-S. (2024). https://doi.org/10.1016/j.inffus.2024.102423	46 citations
3	Anbarasu, K.; Thanigaivel, S.; Sathishkumar, K.; Al-Sehemi, A.G.; Devarajan, Y. (2025). https://doi.org/10.1016/j.biortech.2024.131893	44 citations
4	Yaroson, E.V.; Abadie, A.; Roux, M. (2025). https://doi.org/10.1007/s10479-025-06534-7	32 citations
5	Li, H.; Xi, J.; Hsu, C.H.C.; Yu, B.X.B.; Zheng, X.K. (2025). https://doi.org/10.1016/j.tourman.2025.105179	32 citations
6	Heins, C. (2023). Artificial intelligence in retail – a systematic literature review. https://doi.org/10.1108/FS-10-2021-0210	31 citations
7	Ivanov, D. (2025). https://doi.org/10.1016/j.omega.2025.103356	27 citations
8	Peivaste, I.; Belouettar, S.; Mercuri, F.; Konchakova, N.; Daouadji, A. (2025). https://doi.org/10.1016/j.compstruct.2025.119419	20 citations
9	Sandhu, K. (2021). IGI Global.	18 citations
10	Kumar, R.; Joshi, A.; Sharan, H.O.; Peng, S.-L.; Dudhagara, C.R. (2024). IGI Global	14 citations

Table 4: Ten most relevant papers in the field provided by SCOPUS

Rank	Relevant research paper	Indicator
1	Gadiraju, U.; Balayn, A. (2025). *Enterprise AI*, Springer.	3 citations
2	Kumar, N.; Kumar, R.R. (2025). https://doi.org/10.1007/s11301-025-00575-9	1 citation
3	Deng, K.; Zhang, C.; Song, M.; Hu, X. (2026). *Sustainability* 18(2), 964.	2 citations
4	Latifm, Z.; Mahmood, S.; Sikder, M. (2026). IGI Global.	0 citations
5	Abdelaal, R.M.S. (2026). IGI Global.	0 citations
6	Loske, D.; Klumpp, M. (2021). https://doi.org/10.1016/j.ijpe.2021.108236	54 citations
7	Sharma, A.; Kakkar, P.; Hooda, S.; Kaswan, M.S. (2026). https://doi.org/10.1007/s43069-025-00582-2	2 citations
8	Ivanov, D. (2025). https://doi.org/10.1016/j.omega.2025.103356	27 citations
9	Yaroson, E.V.; Abadie, A.; Roux, M. (2025). https://doi.org/10.1007/s10479-025-06534-7	32 citations
10	Musakhanova, G.; Kayumova, M.; Akbarova, S.; Eshankulova, N.; Shofiddinova, Z. (2026). *Proc. 9th Intern. Conf. on Future Networks and Distributed Systems*.	0 citations

4.3 Discussion

The two searches made in SCOPUS complement and improve the search made by ChatGPT in two separate ways. The complementarity resides in the fact that the search made by ChatGPT names four papers that are not included in the SCOPUS database. Also, in SCOPUS it is possible to find the name of the authors of one paper that ChatGPT defined as "Anonymous". This complementarity may point to be aware of the risk when uncritically trusting results provided by ChatGPT (or any other GenAI tool). In terms of quality of results, databases like SCOPUS are the more reliable source of information on research articles etc. However, using both ChatGPT and SCOPUS as research tools and putting together the results of both experiences not only assures research quality, but increases significantly research efficiency. This improvement comes in two ways:

- Firstly, the study based in citations exposes a set of papers that are quoted, and therefore should look as reliable. The set of papers obtained by ChatGPT may be bolder, but it is more unbalanced with one paper having 2/3 of the quotations and four of them not being included in SCOPUS at all.
- Secondly, the study based on relevance indicates very recent research, which is very important to define the current state-of-the-art in the specific field we choose.

Limitations of our study are related to the fact that it is a very introductory one. To overcome this, this analysis needs to be extended to further steps of the research process, to more GenAI tools and research fields, and to the study of time during research. Particularly, we would like to define the ideal mix between humans and AI in research or by type of research.

5. Conclusions

Similar to other authors, like e.g. Madanchian and Taherdoost (2025), we see quite some potential in (Gen)AI-based support to research. Focussing on the first phase of a research process, idea generation, our study demonstrated that the combination of ChatGPT conversation and SCOPUS search allows to identify a highly relevant research topic and to accompany this by identifying quite relevant literature in an efficient way. However, the quality of the outcome with both tools strongly depends on their human user and his/her interventions. To let GenAI unfold its full potential in supporting research and leaving the researcher to devote much more time to conceptual and analytical work, proper prompting is essential. If the researcher succeeds in this, a conversation with GenAI does not only help to strengthen focus of the research, but GenAI then can provide meaningful summaries from literature review, i.e. state-of-the-art in the field. However, researchers always need to bear in mind that this also comes with certain risks. From our study we saw the discrepancy between ChatGPT and SCOPUS output when identifying relevant literature. Whereas origin of content in the SCOPUS database is pretty clear and transparent, the basis for GenAI operation is not that comprehensible. On the other hand, a proper SCOPUS search is also not as easy as it seems to be. The researcher needs to know his/her field of research quite well in order to be able to provide most promising search terms. So, in the end, a combination of both approaches might be the solution of the future enabling databases like SCOPUS to better understand what the user really is looking for, to better get the meaning behind the terms.

However, none of the tools does perform research alone by itself; as in philosophy a tool might it be AI or a search engine is an assistant not a true researcher. In spite of all its speed, a tool alone is not as good in research as humans are (or can be at least). Human intelligence still is and continues to be the key problem solver, knowledge holder and knowledge user in research. (Gen)AI and its proper use can clearly help in increasing research productivity in terms of both aspect, research quality and research efficiency. At the same time, increased risks associated with data privacy, data provenance, and data integration must remain in focus; policies and controls must protect the individual and the integrity of the operation.

Ethics declaration: For this research, ethical clearance is not required.

AI declaration: This paper was created without any use of AI tools. In order to carry out the underlying research ChatGPT (OpenAI, GPT-5.5) was used as example for an (Gen)AI supported researcher according to the prompts given in Section 4.

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