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Can GenAI Promote Complexity Skills Of Scientists? - A Hypothetical Observation

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Summary

During the corona pandemic, the role of science was seen as something very important in broad sections of society. Unfortunately, this appears to be less the case with regard to climate change. Increasingly, subjective and emotionally based statements are dominating the discussion, which must be viewed extremely critically in view of the complex interactions and extreme effects. On the other hand, great hope is being placed in science to master the complex challenges with the help of artificial intelligence (AI). With the public appearance of generative AI (GenAI) in the form of ChatGPT, a new, partly critical discussion is being held, although AI-based technologies have already made impressive progress as a result of scientific research for many years and numerous developments are already in real use. On the one hand, science is expected to provide insights and recommendations for the responsible use of AI. On the other hand, the use of AI in research work is also discussed critically because it is used, for example, in the application phase of research projects or to evaluate the data obtained and to write down and communicate the results. This gives rise to questions such as "How valid are scientific achievements that are produced with (the help of) AI?" Especially when using generative AI, there is a risk that the own creation process will degenerate due to uncontrolled use, excessive dependency and distortion of results [1], because activities that go beyond routine processes are conveniently left to generative AI, which can be a problem especially when processing complex tasks. An analysis of the authors of around 30 master's theses from 2023 and 2024 in an international engineering master's program showed that around 1/3 of the theses are strongly influenced by GenAI results, recognizable by the usual listing form, the text style and the lack of reference to the task. These papers were also among the 1/3 with the lowest grading. Without guidance on the effective use of GenAI, its use does not appear to lead to improved performance, but instead encourages the unthinking copying of text modules.

On the other hand, observations of the use of generative AI in everyday teaching and research show that GenAI can promote complexity competence in particular when used in a targeted manner on the basis of appropriate training. The authors use GenAI in various contexts of their research, increasingly to support the solution of complex problems and tasks in complex environments. The main area of application is water management and increasingly the analysis of urban areas to adapt to water-related challenges caused by climate change. The main focus here is on the massive impact of extreme weather events such as heavy rainfall and prolonged periods of drought on urban and regional infrastructure as well as forest and agricultural areas. These main areas of application are not only highly complex in thematic terms. Solutions must be implemented at urban and municipal level, and here too, the spatial, infrastructural and organizational environment is highly complex. It is against this background that the observations described in the use of generative AI were made, the theoretical framework described in this article was created and the hypothetical analysis was carried out, for which empirical evidence is still pending, but in preparation.

Keywords: Complexity; GenAI; Loss of Creativity; Loss of Innovation; Prompting

The Initial Problem – Complexity Competence Does Not Follow The Increasing Complexity of The Present

One of the major challenges of the future in the context of work is maintaining the ability to act in complex environments [2]. If this fails, it will place new burdens on employees and demands on organizations. Research from [3] has shown that the ability to deal with complexity is a predictor of work performance. In their studies, this ability was more evident in complex situations in a targeted way than the use of general intelligence. In the year 2000, Steven Hawking called the 21st century in an interview in San Jose Mercury News the century of complexity. In doing so, he referred to the combined interaction of (natural) laws that had previously been considered in isolation and the lack of knowledge of how these fit together and what happens under extreme conditions. Exactly this interaction of various natural phenomena (laws of nature) that have so far been isolated and self-stabilizing under extreme conditions can be seen in the so-called tipping points of climate change. Nine global "core" tipping points, which contribute significantly to the functioning of the Earth system, and seven regional "impact" tipping points, which contribute significantly to human well-being are of great value as unique features of the Earth system, have been identified [4]. Tipping points are followed by inflection points, which signal periods of rapid and intense changes in behavior, perceptions, actions or conditions [5]. Depending on the context, these inflection points can mark irreversible changes (as in the natural sciences or complexity theory) or changes so significant that they could be said to mark paradigm shifts (as in political regime change). Following [6], it should also be noted, that after a certain threshold has been crossed, a self-sustaining acceleration occurs. As in the case of exceeding the 1.5°C limit in connection with climate change, this can have negative consequences if this development is not changed in time (now we know it has negative consequences). Or, with sufficient and early knowledge of the relevant interrelationships, a phenomenon can be consciously imitated and controlled. Major changes such as those needed to combat climate change, are inherently difficult to plan and even more difficult to implement in a democratic process. Nevertheless, there is a large body of scientific evidence suggesting that under certain circumstances, complex systems can undergo deliberately initiated disruptive system changes [7], [8], [9]. For this reason, the mechanisms behind such disruptive system changes, which could be used to initiate changes, are attracting rapidly increasing attention in science. Accordingly, future scientific personnel in particular must have appropriate complexity skills to understand these processes and to find methods to influence them. The extent to which complex knowledge keeps pace with the increasing complexity of the present has been widely studied in the field of project management. For example, [10] leads in his studies to the conclusion that project complexity is a major cause of persistent project failures, as it disrupts project stability. He also notes that the effects and definition of project complexity continue to be discussed in the project management community, and research is still in the process of identifying what knowledge and skills can help project managers deal with project complexity. This suggests that the project participants have insufficient skills in the area of complexity. Another example of the failing effect of complexity can be seen in digitization projects in companies [11] and municipal organizations [12]. In particular, the lack of integration complex future requirements into everyday work is the biggest hurdle to project success [13]. On the other hand, traditional plan-driven models are repeatedly used in construction projects despite the known dynamic complexities, and these projects fail accordingly [14].

At the same time, artificial intelligence provides tools to find better solutions in complex situations when developing measures and making decisions. Human decisions, on the other hand, are often prone to error and subject to cognitive biases, especially when decisions are characterized by uncertainty, urgency and complexity. According to [15], the use of artificial intelligence (AI) can counteract human biases and bring transparency to decision-making processes.

However, systems, particularly generative artificial intelligence systems, are only as good as their training data and can perpetuate biases or even generate and spread misinformation [16]. Although generative AI (GenAI) systems offer opportunities to increase user productivity in many tasks, such as programming and writing, studies show that users work ineffectively with GenAI systems and lose productivity. In [17] four main reasons for productivity losses are listed when using GenAI systems: a) a shift in user roles from production to evaluation, b) an unhelpful restructuring of workflows, c) interruptions, and d) a tendency to use automation to facilitate simple tasks and to complicate difficult tasks (or to avoid difficult tasks). Point d) is of particular importance in the context of complexity, since GenAI can "tempt" us to make our working lives easier and to produce useful results with comparatively little effort, but these is insufficient for complex solutions. This was shown, for example, in a study that examined whether GenAI (here ChatGPT) is better suited than humans for the qualitative analysis of text data [18]. The results showed that GenAI can process large text data sets much faster, but the reliability of the content and thematic assignment was lower than in human analysis, so that the authors concluded that hybrid approaches are necessary, precisely because humans are better than GenAI at identifying nuanced and interpretative topics

AI in science - curse or blessing?

As early as 2023, [19] summarized the main threats posed by the use of generative AI in three points: Risk of job loss, risk of counterfeit content and the risk of sentient machines. In his opinion, the greatest risk of generative AI is that "generative AI will unleash an entirely new form of media that is highly personalized, fully interactive and potentially far more manipulative than any form of targeted content we have faced to date". This danger also applies to scientific work. Studies show, for example, that while the creativity of individuals can be increased through the use of generative AI, the results within a scientific community as a whole lose their novelty [20]. [21] investigated the effect of the uncontrolled use of GenAI when using picture generator Midjourney on the individual cognitive styles in the design process of 30 industrial design graduate students. The cognitive analyses showed that while GenAI significantly increased the frequency of reflections in all student groups, there were minor significant differences between cognitive styles. In addition, two experts evaluated all design outcomes and found no significant differences in novelty, variety, integrity and feasibility between the different

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cognitive styles. The risk of significant bias in beliefs showed [22] in students, which, given the widespread use of GenAI among students, is of crucial importance for the further career path, and in consequence for science too.

The World Economic Forum, on the other hand, sees the use of AI as a boon for science. AI for scientific discovery is recognized here as one of the top 10 emerging technologies of 2024. Generative AI models have the potential to significantly accelerate scientific discovery. By analyzing extensive scientific data sets, formulating innovative hypotheses and identifying promising experimental approaches, they enable researchers to generate research results more efficiently and quickly. In addition, generative AI has already been used to identify connections between different subject areas and to determine findings from the interfaces between the analyzed disciplines [23]. Particularly in creative problem solving, which is an important component in the processing of complex tasks and problems, [24] see a change in the role of humans when Gene-AI-based agents are used to provide support. The agent-based creative systems offer a wide range of possible uses, e.g. for idea generation, evaluation and feedback. The role of humans is changing as the systems become increasingly autonomous. They act more as process managers than as drivers. Specialist knowledge and expertise are still fundamental, but people also need to develop new skills such as rapid engineering and curation.

In addition, there is more emphasis on fostering and exercising humanistic qualities such as empathy and ethics, subjective experience, critical judgment in social and historical contexts, and extrapolation, i.e. imagination beyond data, rather than interpolation, that means the ability of pattern recognition [25]. Nevertheless, the scientific community is afraid of losing trust if AI is used too extensively or incorrectly. [26] explain that trust in technology has so far been closely linked to its reliability. Here, the actual technical reliability meant is equated with a good feeling in the human encounter (e.g. with the manufacturer, the operators or the auditors), and the technical review is omitted. This reveals trust as a typical element of complexity reduction [27], which functions as a mixture of knowledge and non-knowledge [28], [29], [30]. [31] even see this as a central component of digitalization in order to be able to deal with increasing complexity. The more widespread use of AI systems must add this aspect to the previous consideration and reassess reliability. [32] points to an existing skeptical view of AI, namely because "trust in AI systems is not compatible with the lack of transparency that is characteristic of these systems".

At the same time, he rejects excessive euphoria about the potential solutions offered by AI and advocates a balanced approach to AI, summarizing it as "that reasonably dosed trust in AI systems should always go hand in hand with epistemic vigilance". Another question that has arisen in the course of the discussion about the use of AI systems concerns the replaceability of scientists by AI. [33] state that this can only happen if an AI system (e.g. as an agent) imposes the rules of its actions on itself, including changing the rules and determining the means. This is currently and foreseeably not the case. Based on the concept of knowledge and action, humans - despite developments in AI, big data and machine learning - will remain the central actor in research-based knowledge work and cannot be (completely) substituted. For science itself, according to [34] there are not enough studies that have examined the influence of AI on scientific work in detail. For this reason, the focus is primarily on areas related to science, such as knowledge work, in order to transfer the extensive results available here to science.

In addition to the issue of trust, it is becoming increasingly apparent that digital technologies, including the associated infrastructure, are becoming more complex and therefore less transparent. [35] state that with the increasing use of such technologies, knowledge of the functions and interrelationships behind the system is reduced and the balanced approach, preferred by [32] is made more difficult or even impossible. As a consequence, one side categorically rejects such systems, while the other side is convinced of the results (however they were achieved) and has blind faith in them. This can become critical if AI-based systems also influence or even take over complex decisions, as is increasingly the case in application processes [36] or in a scientific context, when AI-generated results are not questioned or verified

Increasing complexity of reality vs. complexity of information systems / AI / organizations

In the development of information systems (including AI), the relationship between task complexity (which describes the goals/results that an IT solution should achieve) and the associated information process (result output) is crucial for the quality of results and usability by the user. Although the creation and use of IT in the execution of tasks is a central area of research in the field of information science, a better understanding of task complexity should be of great benefit to researchers in this field. However, this proves difficult because there are no adequate consistent definitions for it, although there is good guidance in other fields such as behavioral science. This is even more important to keep in mind as the use of generative AI increases and expands to all (complex) economic and social sectors. Against the background of complexity challenges, it is crucial to understand how generative models produce results in order to build trust and understand their behavior in real-world applications [37]. Without knowledge of the (real) complexity conditions, however, it is not possible to use generative AI in a targeted manner.

Using the example of process system engineering (PSE) [38], the importance of aligning GenAI capabilities with the multi-scale requirements of PSE, ensuring robustness for greater safety and trust, managing data availability and heterogeneity, and developing relevant evaluation measures and metrics. On the other hand, the role of multimodal LLMs in improving solution strategies in PSE was particularly emphasized. Multimodal structures play an important role in the context of complexity.

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Organizations are increasingly operating in a complex environment. In order to cope with this, they increase their internal complexity to such an extent that the requirements of the environment can be met appropriately [39]. The effects of climate change in particular are increasingly ascending the complexity of the perceptible world, which is often the subject of research in research organizations. It can therefore be assumed that a similar adaptation of internal complexity to a complex environment will also take place in research organizations. Particularly affected by increasing complexity due to climate change are urban spaces, an increasingly interdisciplinary field of research, which already face major challenges due to inherent processes of managing interrelationships between population, infrastructure and institutions, and will experience an enormous increase in complexity due to the additional pressures of climate change [40]. On the other hand, a study by [41] shows that study participants with lower cognitive complexity are less likely to believe in anthropogenic climate change than those with higher scores. This clearly showed that study participants with higher cognitive complexity were more likely to believe in climate change when they were exposed to a presentation of opposing arguments (i.e. misinformation) along with the correct facts about climate change. In contrast, study participants with lower cognitive complexity were more likely to believe in climate change when presented with climate change facts on their own. In the study by [42] it emerged from the example of spatial planning that the optimum result can only be achieved if several concepts of complexity theory are taken into account. Overall, several levels of complexity come together in climate change, which cannot be adequately addressed with conventional, topic-focused research. In one research project, [43] emphasize the finding that the necessary adaptation governance in response to climate change is highly complex, even at a small-scale level, and can only be effectively addressed by inter- and transdisciplinary research. Similar experiences were also made by [44], [45].

Environmental and resource issues in particular are closely linked and interdependent. In order to understand these challenges and mitigate their consequences, interdisciplinary research and research-based decision-making are required. Taking the development of the research system in Finland between 1990 and 2010 as an example, [46] shows how research in the field of environmental and resource protection, which was previously sectoral, i.e. subject-related (monodisciplinary), had to develop horizontally, i.e. across sectors (interdisciplinary), due to increasing complexity. He showed that the prioritization problems between horizontal and sectoral research resulting from the increasing complexity led to friction, so that the self-organized change sought by the initiators was not achieved. One of the reasons for this was that formal aspects of the change, such as the allocation of financial resources, had to be adjusted, but the necessary complexity competence of those responsible, i.e. the management of uncertainty, interrelated problems and difficult problems, was not adequately achieved. A key unmet objective was to enable greater multidisciplinary diversity compared to individual research projects in order to deal with complexity. However, research projects are strongly dependent on their source of funding, which, without targeted management of interdisciplinarity, has led to fragmentation rather than the promotion of appropriate cooperation between disciplines. The conclusion of this study is that the transition to more horizontal (interdisciplinary) structures within the research system, the maintenance of thematic and temporal coherence in financial instruments and a deeper understanding of internal interactions in the research system are all crucial elements that contribute to the development of complexity competence in research management. Without overarching control, there will be no transformation in this direction, and thus the necessary development of complexity competence will not take place.

Added to this is the increasing thematic complexity, which must also be recorded and analyzed. The acquisition of complexity competence not only supports interdisciplinary research, but also promotes the transition to sustainability in a broader context. It is not a new insight that corresponding (systemic) skills are necessary for complex tasks and challenges. Especially in complex megaprojects in the field of construction and IT, numerous studies and publications are known that have examined the consequences of a lack of complexity competence (e.g. [47], [48]). What do these findings mean for future research competence and what role can/must GenAI play in this?

Tomorrow's research - tomorrow's expertise?

If you enter the term "research competence" in science-related search engines, you will receive several thousand to several million results, depending on the language. It is noticeable that there is hardly a uniform definition, but that research competence is discussed from a wide variety of perspectives and specialist disciplines. In an arbitrary selection as a random sample from the results of the search engine query, [49] state that aspects such as independence, search, initiative, experimentation, practical activity, a situation of uncertainty, collaboration, the existence of different points of view and contradictions are key concepts of research competence. [50] have attempted to develop a Research Competencies Scale (RCS) to make research competence measurable. In the course of their research, they identified various deficits which, in their opinion, indicated a lack of research competence (e.g. after reviewing published articles in specialist journals by experts, they came to the conclusion that "a large proportion" of printed papers should not be published (cited in [51]), or that according to [52], the majority of researchers reviewed did not report statistical power, effect sizes or psychometric properties of the instruments). In their study, [50] described four research competencies:

i. Generating research ideas/literature research

ii. Research methodology/processes

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iii. Research ethics and

iv. Dissemination of research results/scientific writing.

On this basis, 69 items were identified in this six research areas:

i. Research inquiry/literature research

ii. General research methodology/processes

iii. qualitative research methodology/processes

iv. quantitative research methodology/processes

v. Research ethics and

vi. Dissemination of research results/scientific writing).

[53] also created a research literacy evaluation tool for the education sector to assess aspects such as the proposed use of results, target population, conceptualization of the construct, instrument format and creation of validity evidence. The results showed that these instruments are used both to assess the acquisition and mastery of research skills and to evaluate the effectiveness of proposed interventions/measures.

As GenAI enters society, business and ultimately science, the question arises as to whether the current understanding of research competence (and thus the education and training of students and young researchers) is sufficient to meet the demands of a world that is increasingly driven by GenAI [54].

Use of GenAI in science - an approach

In science, generative AI is expected to revolutionize engineering practices, research and education [55], [56]. In particular, GenAI shows great potential in supporting and improving engineering design, with tools such as machine learning and generative algorithms expected to streamline the solution of complex problems and increase creativity [57]. Accordingly, researchers and teachers are calling for greater integration of generative AI as part of the future direction of research and teaching. Initial studies on research experiences paint a differentiated picture. [58] identified three perception clusters among Danish researchers using exploratory factor analysis: "GenAI as a workhorse", "GenAI only as a language assistant" and "GenAI as a research accelerator". Different opinions on the impact of GenAI on research integrity were identified. Language processing and data analysis were generally rated positively, while the experiment design and peer review tasks were more likely to be criticized. [59] was able to determine among Bachelor students that the use of ChatGPT in technical design tasks was used in different ways. Around 60% of the approximately 400 respondents stated that they used GenAI to a considerable extent in their projects, and around 40% saw limited or no benefit in its use. A specified analysis with NotebookLM from Google of 51 selectively chosen special articles published between 2020 to 2024 were done by the authors on the topic of AI or GenAI in research provided an initial overview of the use, benefits, challenges and risks; the results are summarized in Table 1.

Table 1: Use, benefits, challenges and risks of GenAI in science.

Aspect	Contents	Source
Application of Standardized Research Methods		
Qualitative research	GenAI tools can support transcription, coding, thematic analysis and visual analysis of qualitative data	[43]
	For example, ChatGPT has been used in studies to improve coding efficiency and to facilitate data exploration in thematic analysis.	[43]
	GenAI tools can identify latent themes, connections and subtleties in data that a purely human analysis might miss.	[43]
Quantitative research	GenAI tools can be used to support statistical analyses.	[43]
Literature research	GenAI can systematize literature searches by searching large volumes of abstracts and identifying relevant studies. This can help researchers to reduce the "hurdles" associated with manually reviewing large volumes of literature	[44]
Text creation	GenAI can be used to support standard texts	[45]
Research questions	GenAI can be used to generate new research questions	[45]
Creative freedom	The automation of routine research activities through GenAI can give researchers more time for creative and innovative tasks	[46]
Challenges and Risks		
Replicability and consistency	The replicability and consistency of research results obtained with the help of GenAI can be a challenge	[43]
Ethical implications	The use of GenAI in research raises ethical questions, such as data protection, bias and responsibility for the decisions made by GenAI	[43], [47]
Black box problem	The results of GenAI models are often difficult to interpret and understand	[48], [46], [49]

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Success factors		
Competencies in dealing with AI	Researchers need a solid understanding of how GenAI works and the methods involved in order to use these tools effectively and responsibly	[45], [47], [49]
Transparency and explainability	Transparency about how GenAI models work and the explainability of the results they generate are important for acceptance of and trust in AI	[17], [48], [49]
Interdisciplinary cooperation	Collaboration between researchers from different disciplines, e.g. computer science, ethics and social sciences, is important to address the challenges and opportunities of using GenAI in research	[50], [49]

Despite the potential outlined in Table 1, there are only a few published studies that describe the precise application of GenAI in quantitative data analysis [60]. The authors research on which this article is based has confirmed this. Despite extensive research in November/December 2024 in databases such as Elicit, Semantic Scholar and Google Scholar, only 51 qualitatively acceptable publications could be found. This shows that the use of generative AI in research is still at an early stage. The few publications and this small study already show a wide range of possible applications and potential. There is a strong need for further research to deepen and improve the application of GenAI in various research methods [60]. In addition, the development of best practices for the use of GenAI in research, taking into account ethical and data protection aspects, is necessary [60], as well as determining the effects of the use of GenAI on the world of work in research, e.g. with regard to working conditions and the qualification requirements of researchers [34]. As a possible consequence of the increased use of GenAI, job profiles may change, e.g. in the field of prompt development and AI training (this also affects research) [68], [64]. This also means that there may be a change in work processes, the focus is likely to shift from the execution of routine tasks to the control and monitoring of AI systems [68], [64].

In terms of innovation and creativity, it is assumed that GenAI can accelerate innovation processes and help organizations to develop new ideas, products and business models [68], [67]. Initial studies, e.g. by [69] on the use of GenAI in the development of innovative business models show that GenAI can significantly influence business models in all industries in the areas of value creation innovation, innovation of new offerings and value gain innovation. [70] show that GenAI has the potential to drive innovation and growth. They emphasize the need for a balance between innovation and cost efficiency.

Secondly, [70] found that GenAI will play a significant role in the provision of information in decision-making processes to improve market analysis and R&D functions. However, as in other studies, there is a lack of case-based, quantitatively validated findings. Of greatest importance, the role of GenAI is seen as helping to open up new areas of knowledge by analyzing complex data and identifying new patterns and relationships [60], [71].

In summary, three main aspects for future scientific work can be derived from the author's study. Firstly, there is a lack of meaningful and valid studies on the use of GenAI in research, including an investigation of which GenAI is used in which research areas and how it is used in each case. The second area concerns the question of how GenAI can be used most effectively for the various scientific tasks. The third aspect revolves around the question of which skills scientists need to acquire in relation to GenAI in order to be able to adapt to the emerging developments. The use of generative AI in research offers enormous potential, but also poses challenges and risks, as outlined before. By overcoming these challenges and promoting the necessary skills and framework conditions, GenAI can become a valuable tool for research and contribute to new scientific findings and innovations.

Why correct prompting promotes complexity competence

i. In order to answer the question "Can GenAI promote complexity skills in scientists?" on the basis of the results presented on the analysis of complexity and GenAI use in science, an evaluation of the 51 selected sources examined on prompt structure was carried out using again NotebookLM as a supporting system. The analysis shows that prompt structures should be clear, concise, specific and contextual. It should provide the GenAI model with all the necessary information to understand the task and generate the desired output. Effective prompting therefore requires a combination of technical skills and creative thinking. Table 2 shows results in detail of the analysis of chosen 51 sources on what constitutes good and successful prompting.

ii. The comparison of the results with the following selected literature studies on complexity competence shows, that there are some overlaps and similarities to good prompting, even if, according to [78] the attempts to record and catalog criteria for complexity competence are still manageable.

iii. [79] describe, for example, that the causal networking of individual functions in IT systems to form new individual functions strengthens the analytical thinking and complexity skills of IT specialists. A comparable effect is expected from good prompt engineering, as asking the right questions also only leads to relevant and meaningful content through appropriate analytical thinking and prior analysis of the task complexity to be processed.

iv. [80] emphasizes the need for multidimensional observation competence in science, which can be significantly improved by the application of GenAI if the required literature work in various dimensions can be considerably shortened due

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to the time savings. In other words, where a multidimensional approach was previously omitted for reasons of cost, this is no longer a criterion for exclusion.

v. For water management, the authors' main field of work, emphasize [81] based on the evaluation of the flood of the century in the German Ahr valley in 2021, that the following factors are decisive for complexity competence in dealing with disasters:

vi. Ongoing monitoring of the institution's crisis management and adjustments based on this,

vii. filling organizational and/or structural gaps and

viii. taking actions other than those learned in education and training in order to deal with the crisis more effectively and/or efficiently.

ix. Here too, good prompting offers the possibility of creating quick and multi-perspective queries to support these three points in their application.

x. [82] make it clear in their focus work on the consideration of complexity in management tasks in the corporate environment, that complexity competence requires a minimum degree of flexibility in order to be able to adapt to the changing complexities of the environment (organization) and adapt if necessary. This is often achieved through experimentation and an iterative approach to solutions and thus corresponds to one of the approaches of prompting described by [75], recommended and listed in Table 2.

xi. In a study on the use of GenAI by visually oriented designers, [83] found that the group studied often have difficulty, identified specific problems in creating and fine-tuning prompts, and the need to accurately translate intentions into rich inputs in GenAI. The authors then developed a tool for multimodal input of prompts with input from the designers. As a result, the designers developed innovative uses of Design-Prompt, including the development of sophisticated multimodal prompts and the creation of a multimodal prompt pattern to maximize the novelty of their designs while maintaining the necessary consistency. This was only feasible because the authors used a structured observational study of the 12 professional designers to identify their intentions in using GenAI, alignment of expectations, and perceptions of AI transparency, and to transfer these to the multimodal input tool.

xii. Similar to [83], [73] has also developed an adapted multimodal input tool. He focused on prompting adapted to systemic coaching by analyzing processes and participants. It is referred to as triadic coaching because, in contrast to the original GenAI and the examples presented, the human coach remains a fixed real partner in the utilization process (triadic = three participants) in addition to the GenAI input tool for the user (coachee).

Table 2: Overview of the results of the analysis of 51 sources for good and successful prompting.

Aspect	Note	Source
Understanding how GenAI works		
Limits and possibilities of GenAI	GenAI is a special type of artificial intelligence (AI) that focuses on the generation of content	[55], [56]
	GenAI is based on large language models (LLMs) that are trained with huge amounts of data	[55]
	Although GenAI models can imitate human-like speech, they lack contextual understanding. They are primarily used to generate text-based output that is optimized for dialogue.	[55]
	It is important to understand that AI should not be seen as the sole source of information, but as a tool to augment human capabilities.	[55]
	The content generated by GenAI should always be critically scrutinized and validated. There is a risk that the models produce inaccurate information ("hallucinations") that do not correspond to reality.	[55]
	Both GenAI models and human users can introduce bias into the interaction process. It is important to be aware of these potential biases and take measures to minimize them.	[55]
	Prompt engineering means asking the right questions to guide the AI to relevant and meaningful content	[55]
	Consideration of token length and task complexity. Prompts that are too long can overload the model, while prompts that are too short may not provide enough information.	[57]
Balance between user intent and model creativity	A GenAI model needs enough "freedom" to generate creative solutions, but at the same time ensure that the answers fulfill the user intent.	[58]
Prompt strategy		
Proceed step by step	The optimal prompt structure for a particular task can often be found through experimentation and iterative adaptation. Testing different formulations and observing the results helps to improve the prompt within a task.	[58]
Prompt structure		

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Prompt structure	Clear and concise structure and presentation of a prompt	[55], [59]
	Integration of explicit end notes, e.g. three dots for the continuation.	[57]
	Knowledge and understanding of the different prompt structures (e.g. zero-shot (zero-shot prompting asks the model to solve a task without prior examples), Few-shot (Few-shot prompting integrates a few examples for guidance), Chain-of-Thought (CoT) (This technique encourages the model to think step-by-step and explain its reasoning. This can lead to clearer, more accurate and more meaningful answers) or Role Prompting [the model is assigned a specific role (e.g. "You are an experienced chef"). This technique can help to influence the style and tone of the output].	[55], [51], [60], [59], [57]
Prompt text	Use clear and specific instructions in the prompt, preferably verbs such as "write", "summarize", "translate", "analyze", etc.	[51], [58], [59]; [57]
	Avoid ambiguity in the prompt to prevent unexpected responses	[51], [58], [59]
	Structure the entries clearly and distinctly with separators	[60]
	The model must be provided with all the relevant information it needs to process the task.	[57]
	If the output is intended for a specific audience, indicate this in the prompt to customize the style and tone.	[60]
Prompt content		
Content delimitations	Use of explicit restrictions to limit the output of the model and increase relevance. This can affect the length of the response, the format of the output [e.g. list, table, poem] or the scope of the topic.	[51], [58],
Content enhancements	Experiment with context and examples to guide the output and help the model understand the background and goal of the task	[51], [58], [60]
	Use keywords, rules, hints or instructions to guide the model and help the model identify the important aspects of the query.	[60]
Prompt further development		
Model improvement	Addition of feedback and examples to improve the model.	[57]
	Archiving of interaction with the model and adjustment prompt if required	[57]
Credibility and improved results		
Credibility	Describe evidence or quotes as an output result to increase credibility.	[60]
Improvement in earnings	Compare the results of different models	[60]
	Use keywords, rules, hints or instructions to guide the model	[60]
	Specify the format of the desired answer (e.g. text, list, table, code)	[57]
	Using diverse language, avoiding stereotypes and critically questioning the results can help to avoid bias.	[60], [58]

Does structured prompting help when dealing with complex conditions? An initial practical test.

In order to subject the initial question "Can GenAI promote complexity skills in scientists?" to an initial small-scale practical test against the background of the literature analysis carried out, students in the "Smart Water" course of the Master's program "Sustainable Water Management and Engineering" at Hof University of Applied Sciences got a task to carry out a complex multi-criteria analysis using the method of multi-level analysis [84], [45] for the digitization of a new sewage treatment plant to be built in Germany (170,000 population equivalents). The result of this analysis is the examination object of the course and is to be submitted as a written report at the end of the semester. The task was presented and discussed at the end of November 2024. After the lecturer presented the wastewater treatment plant project and the method of multi-level analysis, the students were able to deal with the task in class on beginning of December 2024 and develop initial considerations. In the process, it became apparent that there were comprehension problems regarding the complexity of the tasks. In light of this, a teaching unit was added in mid of December 2024, where students were able to continue working on the tasks with the help of GenAI under the instructor's guidance (students primarily used the freely available version of ChatGPT for this).

This teaching unit was used to conduct a survey among students to find out what help GenAI can provide when working on complex tasks. The following identical questions were asked at the beginning of the lesson and after working with GenAI:

i. How well did you understand the overall task of creating a digitalization strategy for the new wastewater treatment plant? (scale of answers => 1 = not understood at all; 7 = fully understood)

ii. How safe do you feel transferring the selected partial task description to create a digitalization strategy for the new wastewater treatment plant? (scale of answers => 1 = not understood at all; 7 = fully understood)

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iii. How safe do you feel defining the selected task description in more detail? (scale of answers => 1 = completely uncertain; 7 = very certain)

iv. How safe do you feel developing goals and questions relating to the digitalization of the selected topic? (scale of answers => 1 = completely uncertain; 7 = very certain)

The following additional questions were asked:

i. How confident do you feel about using generative AI effectively and solving the subtask well? (scale of answers => 1 = completely uncertain; 7 = very certain)

ii. Do you already have an idea of the prompting strategy you will use to complete the subtask?". (scale of answers => 1 = I still don't have a clear idea of what a prompting strategy is; 7 = I still have a clear idea of what a prompting strategy is)

These questions were also asked at the beginning of the lesson and after the tasks had been completed. Figure 1 shows the summarized results of the seven questions asked.

The answers in Figure 1 show the mean values of all 14 students. It shows that the use of GenAI helps to better understand complex tasks. During the task, students were able to ask the lecturer questions and discuss both their content analysis and their prompting steps. In addition, the students worked in pairs, which allowed for additional verbal discussion of the task. Further studies will now focus on investigating how important it is to precisely specify promptings and what the next step in reflecting GenAI results to increase understanding of complexity should look like.

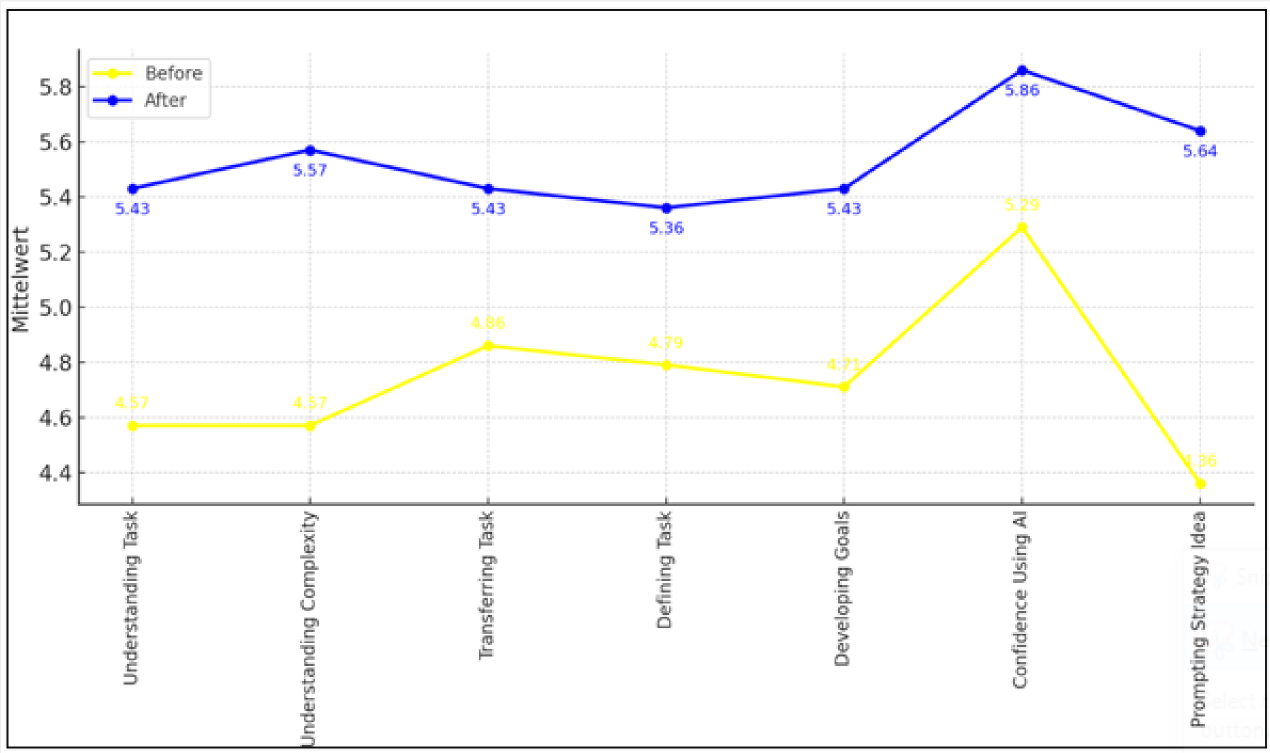

Figure 1: Results of the small survey in the "Smart Water" course December 2024.
(Source: Hof University of Applied Sciences)

Scientific and Methodological basis

The findings and questions presented here serve as a first attempt to categorize subjective observations made when applying GenAI in engineering science. In terms of the GRADE approach (Grading of Recommendations Assessment, Development and Evaluation [85]) for evaluating the quality of evidence from scientific research, the presented results can be assigned to the "observational studies" and thus have a low quality of evidence [86], even if a small survey was conducted among 14 students on the use of GenAI in a complex water management project. The higher the GRADE quality, the lower the risk for the effect evaluation [87-90]. In the strict sense of the GRADE evaluation approach, the presented findings do not represent a strong study based on an experimental design, but observations (including surveys) and knowledge analysis (literature research) were carried out according to scientific criteria.

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Is prompting the new research? A summary

This study investigated the role of generative AI (GenAI) in science and its influence on the complexity competence of researchers. It was found that a targeted use and strategically developed prompting of GenAI can promote complexity competence among scientists, even if some publications mention the risk that creativity and innovative strength may suffer due to the dependence on and promoting convenient use of GenAI tools. Used correctly, GenAI can offer potential for increasing efficiency in various research areas, but can also promote challenges in terms of replicability, ethical implications and the need for interdisciplinary collaboration. Good and strategically sensible prompting can train analytical thinking, the multidimensional consideration of questions/tasks and the necessary factors for dealing with disasters. In addition, prompting can be designed in such a way that it promotes the flexibility required for complexity competence by specifically including experimental and iterative approaches as part of the prompting. On the other hand, the analysis results in Table 2 show that it is of great importance to understand how GenAI works and where its limits and possibilities are in order to obtain an appropriate result for an intended task. However, the presented examples make clear, that, in addition to adapted and effective prompting, suitable multimodal input tools can significantly enhance the process, especially when complex and extensive prompting texts have to be used. If these framework conditions are given, it is precisely the extensive prompting texts that represent an essential building block for the extended development of complexity competence. The creation of such extensive prompting texts requires good preparation in the form of an appropriate analytical and multi-perspective examination of the question or problem description. This kind of thinking process is also necessary when dealing with complex processes. Thus, the initial hypothesis can be regarded as confirmed subject to empirical evidence. Corresponding studies that empirically confirm the assumptions and observations presented are still lacking, but adequate studies are already being in preparation by the authors.

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