Good Prompting = Good Thinking

A Meta-Perspective on Computational Thinking, Model Pluralism, and Creativity

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1. Introduction

The rapid development of generative AI systems has created a new interface between humans and machines. The central instrument of this interface is the prompt, the input formulated by the human to which the AI model responds. In public perception, however, prompting is often reduced to trial-and-error tricks or playful heuristics. This impression misjudges the actual character of the activity. This article firmly opposes the reduction of prompting to mere tricks and postulates: Good prompting is good thinking. We understand the formulation of a high-quality prompt not as a purely technical instruction, but as an act of cognitive craftsmanship—an externalization and refinement of one's own thought process. In other words, advanced prompt engineering is structurally and functionally isomorphic to established processes of good thinking and problem-solving. The mechanisms underlying an effective prompt reflect the characteristics of elaborate thinking identified over decades by cognitive psychology and problem-solving research (e.g., systematic problem decomposition, abstract modeling, perspective shifting). Prompting makes these abstract cognitive skills directly experienceable, measurable, and trainable in an interactive practice.

In the following, we will unfold this perspective along five central cognitive paradigms that can be addressed through prompting:

(1) Computational Thinking (CT), i.e., the way of thinking in computer science, which can be operationalized and learned through prompting;

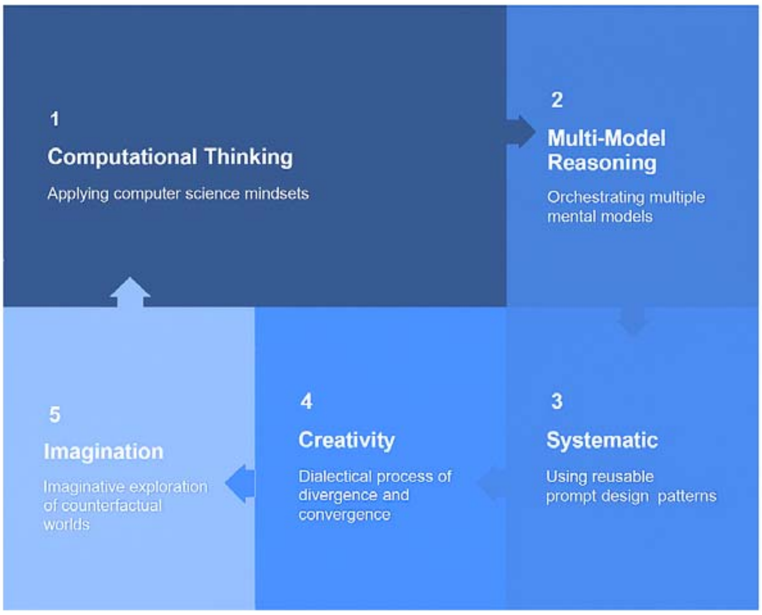
(2) Multi-Model Reasoning, which means orchestrating multiple mental models with the help of AI support;

(3) Systematics, in the form of reusable *Prompt Design Patterns*;

(4) Creativity, understood as a dialectical process of AI-supported divergence and human convergence; and

(5) Imagination, as an imaginative exploration of counterfactual worlds. These paradigms form the chapter structure.

Good Prompting = Good Thinking

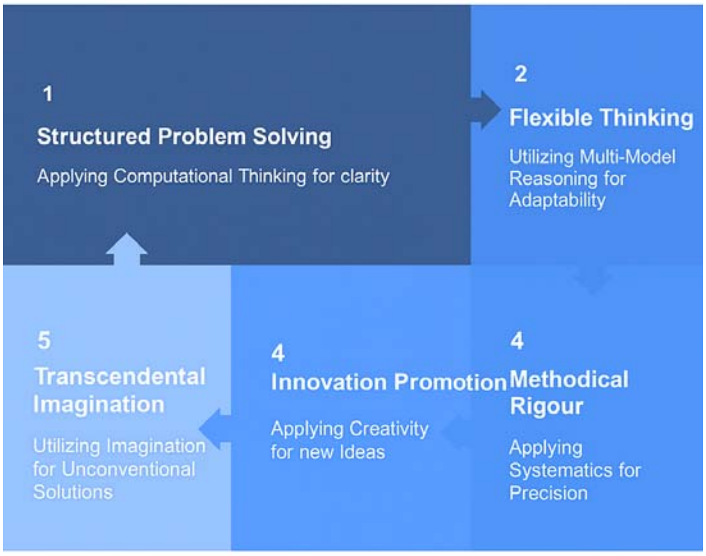


Each chapter combines theoretical foundations with practical examples from various domains—from corporate communication and marketing to psychology—to demonstrate how **prompt engineering functions as a cognitive practice**. Subsequently, didactic implications for education and professional application, as well as consequences for research, will be discussed.

2. Prompting as Cognitive External Representation and Metacognition

The theory of distributed cognition states that cognitive processes are not confined to the brain but are distributed across artifacts in the environment (cf. Hollan, Hutchins & Kirsh, 2000). Thinking, therefore, often occurs in interaction with external aids such as notes, diagrams, or tools. A prompt is a prime example of such a cognitive artifact. By formulating a prompt, complex assumptions, goals, contexts, and side conditions that would overwhelm our limited working memory are externalized into the stable form of written language. This deliberate cognitive offloading—the "offloading" of mental load onto external media—reduces cognitive strain and makes larger problem complexes manageable. In research, cognitive offloading is defined as "the use of physical action to reduce the information processing requirements of a task" (Risko & Gilbert, 2016). By writing a prompt, we transfer sub-steps of thinking from the brain to paper or the screen. This act of externalization has a crucial side effect: It promotes **metacognition**, i.e., **thinking about one's own thinking**. Anyone who wants to write a good prompt must become aware of their own knowledge gaps, implicit assumptions, and goals and make them explicit. One is forced to ask: "*What exactly do I want to know? What information am I missing? In what format would the answer be most helpful?*" This self-reflection corresponds to classic metacognitive monitoring (cf. Flavell, 1979) and trains the ability to monitor and, if necessary, adjust one's own approach.

The Cycle of Prompt-Engineering



The idea of the **prompt as a cognitive tool** can be illustrated with everyday examples. Just as an engineer sketches on a whiteboard to think through a problem, or team members develop a shared diagram in a meeting to align their thoughts (cf. Jensen et al., 2022, on the influence of such artifacts on organizational cognition), the person using a prompt externalizes their thought process in text form. Andy Clark and David Chalmers argued as early as 1998 that external media—such as an Alzheimer's patient's notebook—can become part of the thinking process itself. In this sense, a well-structured prompt extends our cognitive system (Human+AI) analogously to a thinking partner or a mental tool. Prompting thus becomes an interactive cognitive prosthesis, which, according to Clark & Chalmers' Extended Mind thesis, functions as an extension of our mind.

Finally, formulating detailed prompts forces us to structure our thoughts clearly and express our goals precisely—a skill reminiscent of the **"writing as thinking"** method. Research in writing didactics shows that writing organizes and deepens thought. Similarly, prompt writing serves as a didactic bridge: Abstract cognitive skills like systematic thinking or perspective shifting become directly experienceable and trainable through the practical exercise of prompting.

Example 1: From Instruction to Thought Process (Marketing). A marketing psychologist is tasked with developing a campaign for a new vegan protein powder.

- **Simple Prompt:** "Write five slogans for a vegan protein powder."
- → **Result:** Generic phrases like "Plant-based power for you" or "Naturally strong" (superficial, run-of-the-mill ideas).
- **Elaborate Prompt:** "You are a team of experts consisting of a Behavioral Economist, a Creative Director, and a Data Analyst. For the target group of urban millennials (25-35 years), who value sustainability and efficiency, develop two advertising claims from the perspective of each of these roles. For each claim, explain the underlying psychological principle (e.g., Social Proof, Scarcity, Loss Aversion). Format the output as a table with the columns 'Role', 'Claim', 'Psychological Principle'."
- → **Result:** A structured list of creative claims with explained impact drivers, e.g., "Join the 50,000 athletes who have already made the switch" (Role: Behavioral Economist, Principle: **Social Proof**) or "Your body is an ecosystem. Invest in clean energy." (Role: Creative Director, Principle: **Metaphor**).

Commentary: The second prompt forces the psychologist to explicitly consider her target group, different professional perspectives, and psychological principles of influence—her own thought process is thus made tangible in the prompt, and the result is significantly more nuanced.

Example 2: Real-time Problem Decomposition (Data Science). A data analyst faces the question: "Why is our Net Promoter Score (NPS) declining?" – Instead of asking the AI directly for a blanket explanation, she uses **prompting as a metacognitive roadmap**.
She first asks a metacognitive question: "*What are the typical reasons for NPS declines in our industry?*" and then formulates a corresponding prompt: *»List the five most common general causes for NPS declines in SaaS companies and cite a source for each.«* (→ The AI provides a cited list of known causes from the literature). Building on this, she continues: "*Which of these reasons likely apply to us?*" and gives the next prompt: *»Analyze the following customer feedback dataset [insert dataset] and assign the complaints found therein to the five previously mentioned causes. Indicate how frequently each cause occurs.«* (→ The AI searches the dataset and creates a statistic, e.g., that "30% of comments relate to slow support (Cause: poor customer service)," etc.). Finally, she asks herself: "*What do we do now?*" and prompts: *»Based on this analysis, propose three concrete measures to raise the NPS again—each with measurable KPIs, and prioritize the measures according to estimated effort and impact.«*

– In this three-step dialog, the analyst has **decomposed her problem step by step**, and the AI-supported process made her thought process visible. Each prompt represented an intermediate step in her solution path (research general causes → validate specific causes → generate solutions). This structuring corresponds to the principle of gradual refinement, which is also essential in human problem-solving.

Through examples like these, it becomes clear: The prompt functions as an external representation of our thinking. Similar to a thought protocol, it records the mental sub-steps, making them verifiable and communicable. Prompting thus gives our thinking an explicit form, which not only enables collaboration with the AI but also makes our own cognitive processes reflectable.

2.1. Prompt-Iterations and the Co-evolutionary Feedback Cycle

Effective prompting is rarely a one-time act. Rather, it is a dialogical, iterative feedback cycle between human and AI. In practice, a prompt is often adjusted multiple times until the answer is optimal. Such iterations do not merely serve to correct errors but constitute a co-evolutionary process: With each loop, both the user's understanding of the problem and the model's ability to provide a suitable answer are refined. The human learns from inadequate answers and subsequently specifies their query; the AI "learns" in a way from the more precise prompt and delivers a better answer. This mutual refinement process is reminiscent of *radical feedback* in cybernetic systems (cf. Ackoff, 1971) and iterative design cycles in other disciplines.

Recent research confirms the importance of such iterations for successful prompt engineering. For instance, review papers identify iterative prompt improvements as a central strategy (e.g., Liu et al., 2023) and describe prompting in general as an interactive process in which user and AI converge on a solution. Each iteration sharpens not only the prompt but also the user's mental model of the problem. One could say: *You think your way to the solution through prompt-feedback loops*. This gradual approximation aligns with traditional problem-solving strategies, where one starts with rough hypotheses and gradually refines them (known, for example, as *hill climbing* or *gradient descent* in the computer science metaphor).

The iterative process can also be understood as a learning process: The human receives feedback from the AI on their query and can diagnose, based on the quality of the answer, where their prompt was still unclear or incomplete. This creates an ongoing dialogue with the model, actively steered by the user (*prompting as a conversation*). It is important to consciously engage with this feedback and systematically improve the prompt—a skill that can also be practiced and developed (similar to revising text drafts in writing didactics).

Example 3: Iterative Precision (Law). A lawyer is researching a legal case in the field of digital copyright law.

- Her first prompt attempt is: "Cases on digital copyright." → The AI provides an unstructured, unhelpful list, as the query is too broad.
- The lawyer refines her query: "List decisions of the Federal Court of Justice on digital copyright since 2015." → The results are now more relevant but still unformatted and non-specific.

- In the third iteration, she focuses further: "Extract the guiding principles from BGH decisions on the topic of 'Liability of platforms for copyright infringements by users' after 2015. Format the output as a list with file number, date, and guiding principle, and cite the source according to APA 7."
- → Now she receives a clearly structured list of the exact key rulings with source citations.

Commentary: Each iteration brought more precision: An unspecific keyword search turned into a precise, contextual instruction. The lawyer had to articulate her information goal more explicitly from iteration to iteration—a learning effect that sharpened her own thought process.

Example 4: Character Development (Creative Writing). A novelist is developing a new detective character.

- First, he tries a simple prompt: "Describe a female detective in the 1940s." → The AI delivers a generic, clichéd profile (e.g., "trench coat, cigarette, hard-boiled").
- In iteration 2, the author adds details: "Describe a female detective in the 1940s who worked as a codebreaker at Bletchley Park during World War II. She is cynical and relies more on logic than on intuition." → The result now has more depth and individuality.
- In iteration 3, he requests: "Write a short scene in which this detective interrogates a suspect. Her dialogue style should be short, concise, and full of allusions to cryptography. She drinks black coffee."
- → Now the character comes to life: The scene is atmospherically dense, the character unmistakable.

Commentary: Through iterative refinement (adding a professional biography, defining character traits, then fleshing out a scene), the author, together with the AI, went through a creative process that purposefully transformed a one-dimensional character into a complex literary figure. Just as in classic creative processes, this success was the result of a sequence of **divergence** (generating ideas) and **convergence** (focusing and elaborating)—here, mediated by iterative prompts.

In summary, iteration in prompting functions as a **resonance chamber** in which ideas are passed back and forth between human and machine until a viable solution emerges. The human contributes judgment and contextual knowledge; the AI provides broad factual knowledge and generative capabilities. In each step, one approaches the desired answer in a coordinated manner. This approach teaches important metacognitive skills: to see failed attempts not as failures, but as information on how to ask the question better. Thus, prompting becomes an exercise in fault-tolerant, adaptive thinking—valuable not only in dealing with AI but for problem-solving processes in general.

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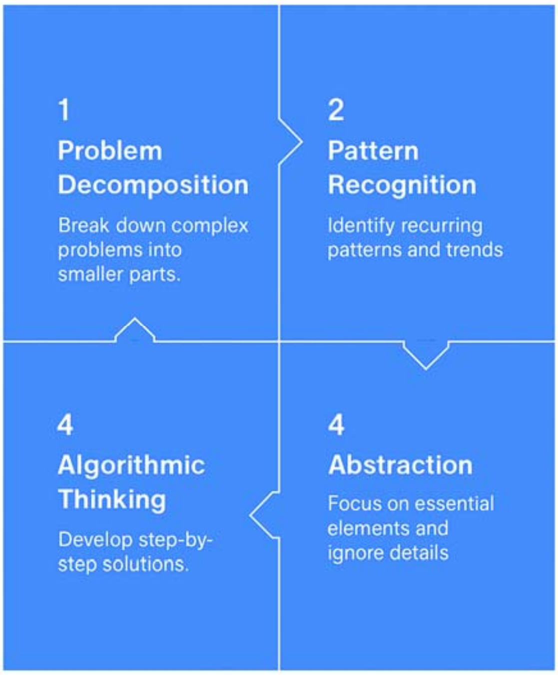
3. Computational Thinking (CT) and Prompt-Engineering

Computational Thinking (CT) is the ability to formulate problems and break them down into sub-steps in such a way that a computer (or algorithm) can solve them (Wing, 2006). This way of thinking is one of the key competencies of the 21st century in education and work, as it promotes structured, logical, and algorithmic thinking (Shute et al., 2017). Prompting operationalizes CT in a tangible way: When we design a complex prompt that directs the AI to a specific task, we implicitly go through the same thought steps as a programmer during algorithm development. In fact, the **four central components of CT** (Grover & Pea, 2013) become directly experienceable through good prompting:

Cycle of Computational Thinking



Problem decomposition means breaking down a large problem into smaller, manageable sub-problems. In computer science, this is known as the "divide-and-conquer" principle. This approach is equally helpful in prompting: Instead of asking a single, potentially overwhelming question, one can divide the query into **modular sub-prompts**. This has several advantages:

(a) It bypasses the context window limitations of LLMs by handling each sub-aspect separately;
(b) It improves logical coherence, as each sub-prompt specifically addresses one sub-aspect;
(c) It reduces the risk of hallucinations because the model is guided step-by-step with verifiable intermediate results, instead of having to solve an extremely complex task at once.

Through problem decomposition, a small pipeline of AI queries is effectively created, comparable to function calls in a program—each performs a clearly defined task, and together they lead to the overall solution.

Example 5: Creating a Business Plan. An entrepreneur asks the AI for help with a business plan for a café. – Instead of directly prompting, "Write me a business plan for a café in Berlin." (to which the AI would likely provide a generic standard plan), he decomposes the task into meaningful steps:
(1) "Create a market analysis for a specialty café in Berlin-Mitte (target groups, competition, trends)."
(2) "Develop a unique selling proposition (USP) and define the target group more precisely."
(3) "Create a financial plan for the first year (fixed costs, variable costs, revenue forecast)."

For each of these sub-prompts, he receives specific, detailed results (such as a list of local competitors with their profiles, several possible USPs, and a tabular cost breakdown). Finally, he combines the partial results—partly manually, partly with another prompt—into a consistent plan.

Commentary: The step-by-step processing ensures that no aspect is forgotten and that the AI, for instance, does not deviate from assumptions made in the marketing section when creating the financial part. Moreover, the founder can check and, if necessary, adjust each section individually. This approach trains structured problem-solving: It corresponds exactly to the procedure of a programmer who first writes modules for input, processing, and output, instead of coding everything in an opaque monolith.

Another component of CT is **pattern recognition**—identifying patterns or regularities that can contribute to a solution. In the context of LLMs, this is particularly evident in so-called few-shot prompting: One gives the model one or more examples so that it recognizes the pattern contained therein and applies it to new inputs. In practice, the user teaches the AI by demonstration. This is analogous to the concept of learning by example: If you show how a task (e.g., summarizing, translating, classifying) is correctly solved, the AI can adopt this structure (Brown et al., 2020). For the human, this means they must abstract the problem and extract a typical example that represents the solution path—also a valuable cognitive process.

Example 6: Standardized Reports. An HR manager wants to write a consistent summary report after every job interview. He already has a well-written sample report and uses it to teach the AI the format: First, he provides the full transcript of an interview as a prompt and adds: "*Sample evaluation: [here follows the sample report for transcript 1]*". Then he continues: "*Now evaluate: [transcript 2].*"
– Result: The AI produces a report for candidate B that matches the sample in style and structure (strengths/weaknesses, cultural fit, etc.).

Commentary: By providing the example, the user has given the model the desired pattern. It is important that he himself first recognized and formulated this pattern—so he had to have an abstracted idea of what constitutes a good report. The AI model can adapt patterns very quickly, but it is the human who decides which pattern is relevant. Few-shot examples can be used in almost all areas: From marketing texts (e.g., provide a sample ad text, then have one written for another product) to psychology (e.g., provide a well-formulated questionnaire item set and have it adapted for a new context). Pattern recognition in prompting thus combines human intuition for style and structure with machine-based reproduction and adaptability.

Abstraction means moving from concrete details to develop a generalizable solution template. In classic computer science, this would be, for example, writing a function that works with placeholders, or defining classes and concepts that are then instantiated with specific values. In prompting, abstraction is shown in the development of prompt templates and personas. Instead of starting from scratch every time, the advanced prompt engineer creates a general template that can be applied to various cases. These templates encapsulate proven procedures and can be reused—an enormous efficiency gain that also reduces *cognitive load*: One does not have to think through every problem from scratch but can fall back on abstract solution structures.

Example 7: Creating a reusable persona. A communications agency wants to develop a generic prompt persona for crisis communication that can be used in various situations. It designs a universal role prompt: *"Persona: You are an experienced PR consultant specializing in crisis communication. Your tone is calm, fact-based, and empathetic. Your goal is to de-escalate and restore trust. Always answer in three parts: (1) Acknowledgment of the problem, (2) Presentation of the measures taken, (3) Outlook on the next steps."*
– It can now use this persona description in any new crisis by simply adding the specific scenario, e.g.: *"... Now, here is the scenario: [insert description of the current crisis]."* The AI will, thanks to the persona guidelines, generate consistent, structured statements that follow the given pattern.

Commentary: The agency has thereby abstracted a prompt template that is applicable across domains. Similarly, a data analyst could develop a template for "Explain a graph in simple language," or a marketing team could create a template for "Social media post in a specific brand style." The ability to form such abstractions is a hallmark of advanced thinking—one recognizes the general in the particular. Prompting actively promotes this: Experienced users collect libraries of abstract prompt patterns (*Prompt Patterns*) over time, similar to how programmers develop libraries of functions and classes. The first systematic collections of such patterns have already been published (e.g., Kocienda, 2024; Oppenlaender, 2024), which shows that the community is beginning to standardize and name recurring problem-solving strategies in prompting.

The fourth component of CT is **algorithmic thinking**: developing a step-by-step solution path that can be followed by an executor (human or machine). In the realm of LLMs, this manifests in so-called Chain-of-Thought (CoT) prompting and related concepts. CoT prompts explicitly ask the AI to reveal its thinking or solution steps sequentially before giving the final answer (Wei et al., 2022). This essentially creates an algorithm in natural language that the model follows.

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Newer approaches like Tree-of-Thoughts (ToT) go even further: The model explores multiple parallel solution paths (branches) and evaluates them to find the best solution. This approach allows solving complex problems via search trees, similar to algorithms in AI (Yao et al., 2023).

Another concept is ReAct (Reasoning and Acting), where the model connects intermediate reasoning with concrete actions—for example, querying an external knowledge source in between—to arrive at a well-founded result (Yao et al., 2022). All these techniques show: One can integrate step-by-step instructions directly into the prompt, which the AI follows, thereby making the prompt resemble a small program.

Example 8: Automated Content Analysis (CT Pipeline). A business doctoral student wants to analyze 10,000 online product reviews for important themes. He designs an **algorithmic prompt plan** with several steps:
(1) **Decomposition:** "Split the following large text block into individual customer reviews." (This way, he gets the 10,000 reviews in a list).
(2) **Algorithmic Thinking & Pattern Recognition:** "For each individual review, perform the following steps: (a) Determine the sentiment (positive/negative/neutral), (b) identify the main themes (e.g., price, quality), and (c) extract an exemplary quote. Output the result in JSON format." (This provides him with a structured JSON line for each review with sentiment, themes, and a sample quote).
(3) **Abstraction:** "Now summarize the JSON results and provide an overview: Name the three most frequent complaints and the three most frequent points of praise and state their respective frequency."

– Through this chain of prompts, he has essentially built an **algorithm framework**: split text → apply function to each unit → aggregate results. The AI follows the instructions and delivers, for example: "Most frequent complaints: 1. High price (23% of reviews), 2. Long delivery time (15%), 3. Poor customer service (11%). Most frequent praise: 1. Product quality (30%), 2. Good customer service (18%), 3. Packaging/Design (10%)." The doctoral student spot-checks the accuracy and thus gains in minutes an insight that would have taken weeks manually.

Commentary: Here, an *in-silico* "program" was written, but entirely in natural language—a great example of how prompting and programming converge. At the same time, the user learns a lot about algorithmic processes: He had to think about control structures ("for each review...") and formats, which mirrors classic programming thinking.

Example 9: Complex Trip Planning (ReAct Style). A user wants to plan a detailed trip. Instead of making a single, comprehensive request, she uses a ReAct-like prompt that combines *reasoning* and *acting*: *"Plan a 3-day trip to Rome for someone interested in ancient history with a budget of €500. Step 1 (Reasoning): Consider which subtasks are necessary (find flights, book accommodation, select sights...). Step 2 (Acting): [search_flights(...)] and [search_hotels(...)]. Step 3 (Reasoning): Based on the options found, create a detailed daily itinerary that considers the opening hours of the Colosseum, Roman Forum, and Pantheon and optimizes walking routes."*

– This prompt first causes the AI to think (Step 1: what do I need?), then to act (Step 2: fictitious calls to search functions—here indicated by placeholders; in an integrated development environment, the AI could actually access a flight search), and finally to reason again and generate output (Step 3: concrete plan). The resulting answer is a structured travel plan per day with times, costs, and sights, which fits the budget.

Commentary: This prompt is conceptually demanding—it requires the model to perform quasi-multitasking and link external information. Although ChatGPT & Co. cannot actually book flights, the example shows the future: Through tools like plugins, LLMs can now indeed perform such actions.

Prompting then becomes the orchestration of thought and action sequences, like an algorithm in natural language. For the user, the ability to write such complex, multi-stage prompts is equivalent to thinking algorithmically—without having to master a formal programming language. This is exactly what makes prompt engineering so attractive as an entry into computational thinking: It lowers the barriers but promotes the same principles of thought.

In conclusion, it should be emphasized: Numerous studies argue that computational thinking is a core competence of the future (Wing, 2006; Shute et al., 2017). Prompting can serve as a training ground here. Learners who write creative prompts unconsciously train the modularization of problems, recognize patterns, abstract solutions, and think in steps—all in a motivating, interactive environment. Prompt engineering thus proves to be a **practical school of algorithmic thinking**. Or to put it more pointedly: Anyone who writes a complex prompt is already programming—just in everyday language. This potential, in particular, should be utilized in education (see Section 8.1).

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4. Multi-Model Thinking: Orchestrating Cognitive Model Plurality

Humans often solve complex problems by developing and weighing **multiple mental models** or hypotheses in parallel. In psychology, one speaks of mental models (Johnson-Laird, 1983)—internal representations or theories that are meant to explain how a particular system works. Epistemically mature thinking is characterized by considering alternative models instead of prematurely clinging to a single viewpoint. However, human thinking naturally tends towards confirmation bias: We preferentially seek information that supports our existing beliefs and ignore contradictory evidence (Nickerson, 1998). Prompting offers a way to actively counteract this bias by specifically instructing the AI to generate different, even contradictory, perspectives or solution proposals. This forces oneself to look beyond the horizon of one's own assumptions and to train cognitive flexibility.

Multi-Model Thinking here is meant to describe the ability to coordinate multiple thinking scenarios—be it different disciplinary models, diverse stakeholder perspectives, or competing hypotheses. The AI can serve as an orchestration tool: The human determines which variety of perspectives should be generated, and the AI delivers the corresponding elaborations. By externalizing the confrontation of different models, one avoids one's own thinking getting too comfortably stuck in a single thought-groove. Instead, a dialogical field of tension is created in which models can complement or be controversially discussed.

Example 10: Scenario Planning for a Product Launch (Corporate Communication). A team is planning the market launch of a new e-health app and wants to assess the risks.
The prompt requests plurality: *"Create a risk analysis for the regulatory approval of our app. Develop three scenarios: (1) Optimistic – quick approval, what speaks for it? (2) Realistic – approval with conditions, which conditions are likely? (3) Pessimistic – rejection or major delay, what would be the main reasons? Rate each scenario with an estimated probability in percent."*

– **Result:** The AI delivers three clearly separated scenarios: e.g., *Optimistic* (30% probability): authority welcomes innovation, fast procedure as data protection is fulfilled; *Realistic* (50%): approval granted, but only with conditions like additional security verifications; *Pessimistic* (20%): rejection due to data protection concerns, as certain AI components are considered a black box.
The team then uses these results to develop counter-strategies with a follow-up prompt: *"For the realistic and pessimistic scenarios, propose a countermeasure for each to still be successful."* The AI recommends, for example, early talks with the authority (for Realistic) or adapting the business model for other markets (for Pessimistic).

Commentary: Through scenario planning, supported by AI, the team received a risk profile spectrum within minutes, which would normally be developed in workshops. Importantly: The human had to initially provide the categories (optimistic/realistic/pessimistic)—that is their expertise. The AI filled these frameworks with plausible content. This process forces one to explicitly think through non-desired outcomes (like failure), which is often omitted in human teams due to bias. Thus, prompting here serves as a cognitive debiasing tool.

Example 11: Strategic Decision-Making (Politics/Public Relations). A political advisor wants to anticipate the public reaction to a new climate law draft. She uses the AI to simulate various actor perspectives:
"Write three press releases on the new climate law: (1) from the perspective of an industry association that sees jobs threatened; (2) from the perspective of an environmental NGO for whom the law does not go far enough; (3) from the perspective of a liberal think-tank that praises market-based approaches but criticizes bureaucracy."
– **Result:** The AI produces three strikingly different press releases, each in the appropriate jargon and tone of the actors. The first (industry) emphasizes "endangering the location and unnecessary regulation," the second (NGO) welcomes the

move but calls for "drastic measures to reduce emissions," and the third (think-tank) praises "innovation incentives through emissions trading" but criticizes "excessive reporting requirements."

Commentary: The advisor thus receives a panorama of possible lines of argument, a preview of the public debate, so to speak. This allows her to prepare her own communication strategy, for example, by having counter-arguments ready or by highlighting consensus-oriented elements in the legislative reasoning. Cognitively, she has performed a perspective shift through prompting: Instead of thinking only from the government's point of view, she has put herself in the shoes of opponents and supporters. This process is analogous to the well-known role-playing in psychology, which promotes empathy and understanding. The AI serves here as a simulator for foreign viewpoints. This is particularly valuable in corporate communication and PR—one can pre-check messages by asking the AI to react "like a critical journalist" or "like a skeptical customer." Prompting thus forces one to perform anticipation and perspective-taking.

Example 12: Multi-Theoretical Analysis (Psychology). A cognitive psychologist is planning an experiment on learning with digital media. To not overlook anything, he wants to include different theoretical viewpoints.
He formulates a prompt that activates three psychological paradigms in parallel: *"Analyze the following research design from three theoretical perspectives: (a) behavioristic – which stimuli and reinforcers are used? (b) cognitive – which mental processes (attention, memory) are involved? (c) constructivistic – how do learners actively construct knowledge in this design? For each perspective, name the opportunities and possible weaknesses of the design."*
– **Result:** The AI delivers three separate analyses: *Behavioristic*: emphasizes, e.g., the role of immediate feedback as a reinforcer, but criticizes a potential lack of intrinsic motivation; *Cognitive*: discusses attention guidance and cognitive load, notes that the content requires chunking; *Constructivistic*: praises collaborative elements and self-activity, but criticizes that too little prior knowledge of the learners is considered.

Commentary: The researcher thus receives a multi-dimensional evaluation draft at the push of a button. Of course, he must check the quality and enrich it, but as a thought-starter, it is worth its weight in gold. Instead of conveniently following only his own preferred theoretical approach, he used the AI to play *Advocatus Diaboli* for alternative theories. This promotes a more comprehensive understanding of the project. In everyday research, literature reviews could be supplemented this way: One asks the AI, for example, to interpret study results from different schools of thought (Freud vs. Behaviorism vs. Neurobiology).

Such applications show how prompting enables a model plurality that would often be unreachable for humans alone in the same depth—if only for time reasons. However, it is the task of the human to select the relevant models and to critically examine the quality of the generated perspectives, so as not to risk an automation bias (blind trust in AI answers) instead of a confirmation bias. Overall, however, prompting shifts part of the cognitive heavy lifting—the "putting oneself in someone else's shoes" and playing through alternative assumptions—to the machine and thus enables faster, broader thinking.

In summary, multi-model prompting serves the purpose of systematically generating and utilizing cognitive diversity. In companies, this can mean conducting scenario planning with AI support (as in Example 10) to develop more robust strategies. In psychology or research, it can mean preserving theoretical diversity and promoting the competition of ideas. In personal decision-making, one could use AI to play through pro-and-con lists or alternative life drafts. But it is always the user who is asked to provide the right impulses—*which* models should be generated—and then to synthesize the results. Prompting thus becomes a mental workshop in which one tries out different tools (models) before deciding on an approach. This fosters a certain humility before the complexity of the world: Seeing how a problem appears from different angles trains critical thinking and protects against premature, one-dimensional solutions.

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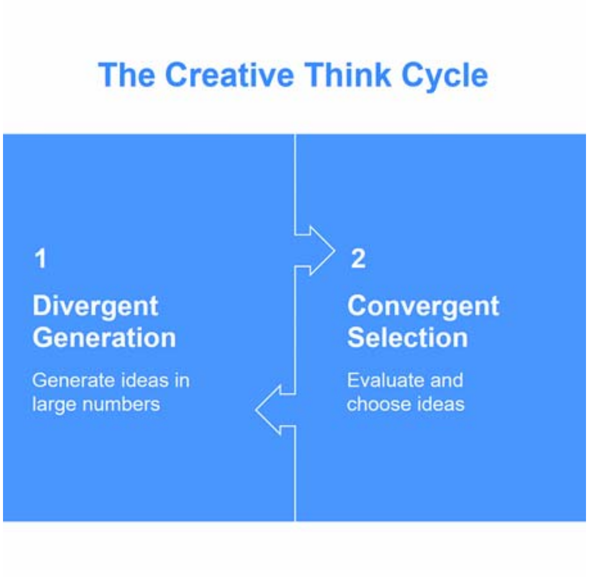
5. Creativity: Divergent Generation and Convergent Selection

Creative thinking is often described as an interplay between **divergent** idea production and **convergent** idea evaluation (Guilford, 1967; Sawyer, 2012). The divergent phase is about generating as many and as varied ideas as possible—thinking laterally, taking unusual paths, piling up options. The convergent phase then consists of sifting through, evaluating, and pursuing the most promising of these options.



Generative AI proves to be an unprecedented **"divergence machine"** in this process. It can generate a kaleidoscope of variations, styles, and perspectives from a single starting point, thus drastically expanding the *adjacent possible* (Kauffman, 2019). What a human creates in a brainstorming session with 10 ideas, a model delivers in seconds in 100 variations—and often with surprising originality.

However, the convergent phase—i.e., selection, evaluation, synthesis, and strategic classification of ideas—remains a domain where the human must retain leadership. After all, recognizing the relevance, feasibility, and value of an idea requires contextual and often implicit knowledge that AI does not reliably possess. But when human and AI deliberately collaborate here, the originality and quality of creative work can empirically increase. Lee et al. (2024) show, for example, that designers who use AI in early idea generation phases achieve more original results in the end—*if* they then strictly select and further develop. Prompting as a creative technique thus means: First let the machine diverge, then converge humanly.

A great advantage of AI is the stylistic and perspectival diversity it can adopt. For divergent thinking, it is helpful to deliberately change styles or pose absurd tasks to explore new paths. With generative models, this can be easily initiated by providing specific instructions that lie far outside one's own comfort zone.

Example 13: Creative Writing with Multiple Styles. An author has an idea for a short story: An AI discovers it lives in a simulation. She wants to make something original out of it. Instead of just using her own writing style, she formulates a prompt as a style experiment:
"Tell a short story about an AI that discovers it lives in a simulation. Version 1 in the style of Philip K. Dick (paranoid, metaphysical), Version 2 in the style of Isaac Asimov (logical, rule-based), Version 3 in the style of Ted Chiang (melancholic, philosophical)."
– **Result:** The AI delivers three distinctly different stories: The *Philip K. Dick version* is dark, surreal, and questions the levels of reality; the *Asimov version* is factual, with a robot detective who deductively uncovers the simulation; the *Ted Chiang version* is pensive, poetic, and focused on moral implications. The author now has a cornucopia of ideas: She might take the metaphysical twist from version 1, combine it with the logical plot framework from version 2 and the emotional depth from version 3—and create her own fourth story of high originality.

Commentary: Without AI, she would probably have tried only one or two iterations. Through prompting, she surprised herself and discovered elements she would hardly have come up with on her own. The divergent phase (three radically different styles) was radically expanded by the AI. The convergent performance (selection and assembly of the best parts) was hers. This approach shows how AI can serve as a creative sparring partner. It is also reminiscent of creativity techniques like "building analogies" or "perspective shifting," only here the perspectives of famous authors are imitated. What is important, again, is the human evaluation: Which version resonates the most? What is cliché, what is genuinely interesting? The AI delivers raw material, the human shapes it into a work of art.

Example 14: Visual Ideation (Design). An architect is designing a concept for a museum of digital art. He wants to develop an unusual style and uses an image generator model (e.g., Sora or Ideogram) via prompt:
"Concept sketch for a museum of digital art. Style: Imagine Zaha Hadid meets ancient Japanese timber architecture. Materials: Bioluminescent concrete and dark wood. Mood: contemplative, futuristic. Output: 10 different exterior views."
– **Result:** The model generates 10 impressive concept images, from organically curved forms to cubist pagodas, all with fused elements of high-tech and tradition. The architect selects the two most interesting designs—perhaps a variant with flowing Hadid lines and one with modular wooden elements—and sketches his final design based on them.

Commentary: Here it becomes clear how AI delivers unconventional combination ideas in the design process (Hadid + Japanese architecture + bioluminescent concrete—a rather outlandish mix that is precisely why it produces a new aesthetic). It is crucial that the architect selects from the 10 results what is viable. The variety of proposals stimulates his creativity; he might see possibilities he hadn't thought of before (e.g., the idea that walls could be made of *glowing concrete*). Such image prompts are the visual equivalent of the textual divergent prompt. In marketing and advertising, something similar could be done: generate mood boards, test logo variations, etc., to then be curated by humans.

Given this potential, the question arises: How can one steer the divergent phase in a targeted manner? For this, some prompt techniques have proven effective for inducing creativity. In the following (Section 5.1), we describe three such techniques as examples: provocation, constraint, and metaphor.

Provocation Prompts: They deliberately turn conventions on their head or formulate absurd assumptions to generate new thought-starters. This method follows Edward de Bono's idea of *provocation* in lateral thinking. By intentionally questioning the obvious, provocation prompts force the model (and the human reader) to break out of habitual thought patterns.

Example 15: A futurologist gives the AI the task: *"Describe a world in which the concept of private property was never invented. What would cities, families, and work look like in such a society?"*.
This provocative "what if" question leads to creative visions beyond our frame of reality—such as cities without condominiums, but only communal spaces, different family structures, other incentives in working life. Such ideas may sound utopian or unrealistic, but they serve to question established assumptions and often open up surprising insights.

In corporate innovation, one could use analogous provocative prompts like: *"What if our main product were banned tomorrow—how would we design our business model?"* The goal is not prediction, but the stimulation of thought.

Constraint Prompts: Paradoxically, an artificial constraint can fuel creativity. When certain obvious solutions are forbidden, one must find all the more original ways (Stokes, 2005). Examples are creative writing exercises like lipograms (not using the letter "E") or limited word resources.

Example 16: A songwriter gives the AI the following strict instructions: *"Write a lyric about loss, but use only one-syllable words and avoid the color black."*. These constraints force unusual formulations. The AI might produce a minimalist-poetic text in which, instead of "black," perhaps "night" or "empty" is used. The songwriter thus gains a new perspective and perhaps a few lines that touch precisely because of their simplicity. In other domains, one could analogously say: "Design a product that works without electricity"—to stimulate innovative mechanics instead of electronics. Or in marketing: "Create an advertising campaign without text, only with images and numbers"—to force non-verbal ideas.

Constraints act like a catalyst: They prevent standard solutions and often lead to creative breakthroughs. Research on creativity confirms that constraints can improve the yield of ideas because they narrow the problem space and thereby intensify it.

Metaphor Prompts (Analogy): The use of metaphors or analogies is a powerful creative tool. One transfers structures from one domain to a completely different one to generate new ideas (Gentner, 1983). Prompting allows us to have the model draw such analogies in a targeted manner.

Example 17: An organizational developer is looking for fresh ideas for the structure of a tech startup. He formulates: *"Design a new organizational structure for our startup based on the metaphor of a mycelial network (fungal network). How do communication, leadership, and growth function in this model?"*.
The AI analyzes features of mycelium (decentralized, self-organizing, interwoven) and projects them onto a company: e.g., complete decentralization of decisions, communication like nutrient exchange among each other instead of top-down, growth through offshoot teams, etc. Even if not all these ideas are 1:1 practicable, they provide inspiring food for thought that goes far beyond common management approaches. The developer could, for example, adopt the principle of forming small, autonomous teams ("cells") that are strongly networked with each other—an approach that might not otherwise have been considered.

Metaphor prompts force the AI to search for structural similarities, which often brings very innovative concepts to light in the output. The beauty is: Even if the analogy is weak, it encourages the human to think more deeply about what is transferable and what is not—this is also a creative process of insight (think of well-known metaphors like "company as a family" or "brain"—each illuminates different aspects).

Overall, it becomes clear that one can steer the type of generated ideas through a skillful choice of prompt technique.

- Should it be wild and radical? → **Provocation.**
- Should it be concentrated and pointed? → **Constraint.**
- Should it be novel through cross-references? → **Metaphor/Analogy.**

In creative professions, such approaches can be used in a targeted manner. For example, an advertising agency could, in a brainstorming session, "add" an AI alongside the human teams, which runs through exactly these variation techniques—as an inexhaustible source of raw ideas, so to speak.

It remains important that a curating instance (usually the human) separates the wheat from the chaff. AI generates everything possible without a standard of value—the banal, the brilliant, and the bizarre. The creative achievement ultimately lies in recognizing and further developing those approaches from this abundance that truly create value or solve the problem. In this interplay, AI and human can thus form a creativity-promoting cycle: The AI delivers quantity and variety in the divergent phase; the human brings quality and meaningfulness in the convergent phase.

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6. Systematics: Design Patterns of Prompting

Scientific progress and professional excellence are not only based on creativity but also on systematics, replicability, and efficient methodology. In software development, one speaks of Design Patterns: reusable solution patterns for common problems (Gamma et al., 1994). A similar trend is emerging in prompting. With increasing experience, Prompt Design Patterns are crystallizing—that is, proven approaches that can be standardized and reused. This makes the interaction with AI more systematic and scalable. Single-case tricks are evolving into generalizable methods that can be documented, taught, and implemented organization-wide.

We have implicitly seen some well-known prompt patterns, or they are actively discussed in the community:

For example:

- Role Prompting (putting the AI into a specific role to steer the output style),
- Step-by-Step Prompting (instructing the model to provide a solution path in individual steps—related to CoT), or the
- Delphi Pattern (the AI simulates an expert panel, as in Example 7 with the lawyer/developer/manager discussion).

These patterns make it possible to handle complex tasks by providing structured frameworks.

Newer patterns are developing rapidly: An interesting example is the "Flipped Interaction Pattern": Here, the tables are turned, and the AI is instructed to ask the user questions to better understand the request. Instead of passively feeding the AI, it becomes a proactive, Socratic partner. This pattern can help to clarify fuzzy problems together with the AI—a procedure that is particularly useful when the user does not yet know exactly what they need. Overall, there is great potential in identifying such patterns: It creates a common language for prompt engineers (comparable to design pattern catalogs in software engineering) and makes the solution process more efficient.

Example 18: Creating an expert report (Pattern Chain). A compliance officer is to write an internal report on the introduction of biometric authentication. He uses a chain of prompt design patterns:
First, the Delphi Pattern – *"Simulate a discussion between a strict data protection lawyer, a pragmatic software developer, and a user-centric product manager about the introduction of facial recognition for authentication. Provide the conversation protocol."*
→ The AI delivers a fictitious but well-founded dialogue in which concerns, technical feasibility, and user acceptance are discussed controversially.
Next, he applies the Step-by-Step Pattern – *"Analyze the above transcript and create a structured risk report with bullet points: Identify main concerns, possible countermeasures, and remaining uncertainties."*
→ The AI generates a structured list of key risks (e.g., "Data protection: storage location of biometric data – countermeasure: local storage," etc.).
Finally, he uses the Role Pattern – *"Summarize this report in an Executive Summary for the board. Tone: concise, solution-oriented, without jargon."*
→ The result is a management-friendly overview.

Commentary: By combining several patterns, the compliance officer has created a high-quality report step by step. Each prompt was clearly focused and reusable—for example, he could recycle the Delphi setting (lawyer vs. developer vs. product manager) for other tech-vs-compliance questions in the future. This example shows the added value of pattern thinking: Standard procedures are created that ensure quality and can be efficiently reproduced. Instead of relying on random prompt ideas, one works methodically. In an organization, such patterns could be collected in a knowledge base (see Section 8.2).

Example 19: Project start with Flipped Interaction. A project manager is tasked with introducing a new CRM system in the company. He knows that thorough planning must consider many aspects but is unsure where to start.
He tries the Flipped Pattern: *"I am starting a project to introduce a new CRM system. Your role: an experienced project management coach. Task: Ask me the 10 most important questions I need to answer at the beginning to create a comprehensive project plan. Number the questions and wait for my answer after each question before you proceed."*
– **Result:** The AI coach first asks, for example, "1. What specific goal is to be achieved with the new CRM system (e.g., efficiency increase, better customer data...)?" The PM answers this question (in dialogue with ChatGPT). The AI then asks the next question, "2. Which departments and user groups will primarily use the system?" and so on, through all critical planning questions: budget framework, timeline, risks, change management, etc.
At the end, the project manager has not only thought through all important aspects but has also already worked out a lot of project substance in his answers.

Commentary: This procedure reverses the usual questioning—instead of "*Give me a plan,*" he says, "*Ask me about everything important.*" This requires some courage from the prompt designer to admit a gap (admitting that one needs guidance) but is rewarded with a customized question framework. It resembles a checklist or a consultation.

The Flipped Interaction Pattern is particularly helpful for unclear problems: When you don't even know what to ask, you let the AI help structure the problem. In a corporate context, this can be enormously useful, for example, to develop a requirements catalog (the AI asks systematically as a business analyst), or in risk analysis (the AI asks like a risk manager about possible risks). This pattern impressively shows how flexibly AI dialogues can be designed—the AI does not always have to be the answerer; it can also be the questioner and sparring partner.

You can see: Systematics in prompting means moving away from ad-hoc procedures and instead building method toolkits. Instead of approaching every problem "creatively" from scratch, the experienced prompt engineer identifies patterns: "*Ah, here it helps to first take a Delphi step, then a step-by-step.*" or "*For this creative task, I'll first use provocation, then constraint.*" This methodical approach increases the success rate and consistency. It also enables better communication about prompts: If two colleagues both know what is meant by "*Do the Flipped-Pattern,*" they can exchange ideas and compare results more quickly. Initial overviews of such patterns and techniques are already being published and discussed (e.g., Oppenlaender, 2024; Liu et al., 2023). This indicates that prompt engineering is evolving from an art to an engineering discipline with best practices. Of course, there remains room for intuition and context adaptation—as in any design process—but the foundation is clearly defined strategies.

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7. Imagination: Imaginative Exploration Beyond Empirical Boundaries

The psychologist Lev Vygotsky (2004) viewed imagination not as mere escapism, but as an essential human ability to productively recombine experiences to create possibilities. Imagination allows for the mental transcendence of current reality: to ask "*What if...?*" without being constrained by momentary empirical limitations. Prompting can serve as a kind of imagination prosthesis: With AI support, highly complex hypothetical or counterfactual scenarios can be designed and explored. It is important that these simulations do not drift into complete arbitrariness—they are based on the model's vast knowledge base and are therefore often internally consistent and surprisingly plausible. As a result, AI-generated scenarios can serve as a starting point for scientific hypotheses, ethical debates, or artistic visions.

In other words: While creativity (Chapter 5) expands the space of the possible by recombining what exists, imagination goes a step further and creates spaces that are radically different from the known. It is about thought experiments that change natural laws or fundamental societal assumptions to see "what happens then." Scientists use such things as thought experiments (e.g., Einstein, who imagined riding on a beam of light), ethicists consider dystopian or utopian futures to test values, and authors, of course, create sci-fi or fantasy worlds. LLMs can greatly enrich such thought experiments by taking over the detail work: They "fill" the vision with coherent details that our limited imagination might overlook.

Example 20: Counterfactual Science (Physics). An astrophysicist wonders what would happen if a fundamental constant of nature were different. She prompts: *"Design an alternative cosmology in which the gravitational constant is 10% weaker than in our universe. What three primary consequences would this have for the development of stars, the formation of galaxies, and the possibility of life-creating planets? Justify the conclusions with physical principles."*
– **Result:** The AI generates a fascinating thought experiment: Stars would be less stable and would have to accumulate more mass to shine (which might lead to fewer, but more massive stars), galaxies could be larger and more loosely bound because gravity clusters less strongly, and planetary habitats could look different—e.g., planets would form at a greater distance from stars, or life would have different evolutionary conditions due to lower gravity. Each conclusion is justified with known physical laws (e.g., how hydrostatics in stars changes).

Commentary: For the astrophysicist, this is an excellent stimulus—possibly nothing entirely new that she could not have worked out herself, but it saves enormous time and may suggest aspects (e.g., effects on galactic structures) that she had not initially focused on. Such a prompt scenario can serve as a starting point for serious research: One could quantify certain statements of the AI or test them in simulations. Through the AI, she quickly got a consistent picture of a foreign physics, which serves as an intuition and a qualitative sketch.

In other sciences, one could proceed analogously: "*What if Darwin had not discovered natural selection, but [counterfactual assumption]...*"—to test theories. Important: AI does not replace validation here (the physicist must check if the AI's fantasy is truly physically consistent), but it provides a first idea sketch to build upon.

Example 21: Ethical Simulation (Behavioral Economics/Politics). An ethics council wants to explore possible future problems with autonomous weapon systems. It uses prompting to create a social simulation: *"Simulate a hearing before the UN Security Council in the year 2040. Participants: a general, a human rights lawyer, an AI ethicist, and the diplomat of a small country. Topic: an international incident in which an autonomous weapon system failed. Write the dialogue that reflects the different values and interests of the participants."*
– **Result:** The AI generates a multi-layered conversation. The general, for example, defends the use of autonomous

weapons to save his own soldiers' lives and plays down the incident as a technical glitch; the human rights lawyer calls for a ban on such systems and emphasizes the civilian victims; the AI ethicist discusses responsibility and the lack of transparency in the decision-making algorithms; the diplomat of the small country describes vividly how his country got caught in the crossfire and pleads for international regulation. This simulation contains emotions, arguments, threats, appeals—in short, a realistic scene of a future conflict.

Commentary: For the ethics council, such a script can serve as a basis for discussing regulation. By honestly showing the extreme positions, the AI makes the dilemma tangible. People can then analyze this fictional debate: Which arguments carry more weight? What compromises would be conceivable? In principle, one has conducted a role-play without having to involve real people. Such simulations are, of course, only as good as the underlying assumptions of the AI (here it draws on existing knowledge about military, ethics, etc.). Nevertheless, they can provide food for thought. Behavioral economists could, for example, simulate: "What happens if a basic income is introduced in a city—have an entrepreneur, a welfare recipient, and an economist discuss it 5 years later." Of course, this is not real evidence, but it helps to play through consequences and possibly generate new hypotheses that can be empirically tested.

These examples illustrate the value of imagination-prompting: It allows the safe exploration of scenarios without real-world risks or costs. One also speaks of "synthetic experiences" gained through simulation.

In pedagogy and psychology, LLMs could be used, for example, to simulate virtual conversation partners (such as a conversation with a historical philosopher or with the "future self" in 20 years), which can be therapeutically or educationally exciting. What is important is a critical distance: The simulated worlds can be internally consistent, but they remain inventions. One must not confuse fiction and reality—a challenge, especially when the AI outputs are very convincing. Nevertheless: Especially in the early phases of projects or research, such an imaginative exploration can uncover stumbling blocks or blind spots before one invests in reality. In terms of the philosophy of science, this is reminiscent of thought experiments, which were often forerunners of real experiments.

In summary, prompting in the sense of imagination offers a kind of **cognitive laboratory** in which one can build alternative realities. Be it out of curiosity (What if the dinosaurs had never gone extinct?), for value clarification (What kind of society would emerge if no one could lie?), or for prognosis (What could democracy look like in 50 years?). This ability to expand our conceptions has great developmental and cultural value, according to Vygotsky—it lets us think beyond the here and now and anticipate innovations in the first place. AI makes these journeys of imagination more accessible and immediate than ever before. We should use them to broaden our mental horizons—always with the awareness that we are playing in worlds of possibility, not in reality.

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8. Didactic and Professional-Practical Implications

After having looked at prompt engineering from various cognitive science perspectives, the question arises: What does this mean for education, organizations, and research? If good prompting represents good thinking in many facets, we should specifically promote and use it. In this chapter, we outline some implications.

Given the connections described above, it seems natural to anchor prompting as a core competence in educational contexts. Students should learn not to treat AI merely as an oracle to which one throws a question, but as an interactive tool that mirrors and improves their thought process. Didactically, prompting can be used to promote computational thinking, metacognition, and critical thinking. For example, in a computer science seminar, tasks could be set where students must not only present the AI's answer but also explain and justify the prompt they wrote—including the iterations they went through. This makes their thought processes visible and assessable. In humanities seminars, one could have ChatGPT generate, for example, literary-theoretical positions on a text, and then discuss: Why did the AI interpret it this way? What does this say about our own interpretative frameworks? Here, too, the AI output becomes a mirror in which learners test their understanding.

Also important is the training of judgment in dealing with AI-generated content. Students must learn to critically question AI answers, to check for possible errors or biases, and to verify them. This can be addressed didactically, for example, by intentionally generating false or biased answers and having the learners correct them. The goal is an active AI competence: knowing how to get good results and recognizing where the limits of AI lie.

Initial proposals to explicitly include prompt engineering in curricula already exist (Federiakin et al., 2024). There, prompting is defined as a new key qualification of the 21st century—comparable to earlier "digital literacies." It requires an understanding of the basic mode of operation (e.g., that a small word difference can have huge effects), of the ethical implications (e.g., no forbidden prompts, fairness), and of the strategic application (when do I use AI at all and when not?). A challenge is the form of assessment: How does one measure prompt competence? Possible approaches: practical prompting projects in which students work on a complex task with AI and document it; reflective essays on the prompting process; or even specially developed prompting exams where one has to show how to turn a mediocre AI draft into an excellent answer through iterative improvement.

Another aspect: Democratization of cognitive skills. Prompting can make abstract skills tangible—e.g., logical thinking in CoT prompts, perspective shifting in multi-model prompts, etc. This makes these skills trainable at a lower threshold. Students who might struggle with formal logic could develop an intuitive understanding of logical sequences through playful interaction with ChatGPT (e.g., by teaching the AI to solve a riddle in steps). Prompting could thus become an integral part of interdisciplinary learning settings, as it builds bridges between computer science, psychology, language competence, and subject-specific knowledge.

Finally, such training prepares students for the job market: AI tools are entering almost all industries. Prompt Literacy—the mastery of "AI address"—will likely become a key competence for many professions. It determines who can use AI as a *lever* for higher productivity and creativity and who cannot. Universities and schools have the task of building this literacy so that graduates are not just *consumers*, but competent users of AI. This also includes a set of values: when one should use AI (e.g., to generate ideas), and when consciously not (e.g., to train original own skills, like learning to calculate without a calculator).

A possible didactic scenario: A course "Thought Processes with AI" for first-year students of all disciplines, in which students are playfully introduced to various problem-solving situations—mathematical, textual, argumentative—and always have the task: *Solve it with and without AI, compare, reflect*. Such approaches could promote early meta-thinking and reduce both fear of contact and false expectations (AI is not infallible).

In the corporate world, structured prompting opens up numerous efficiency and innovation potentials. Communication, both internal and external, can be made faster, more consistent, and even more personalized with AI support. On the one hand, prompting allows for very fast hypothesis testing in marketing: Instead of spending weeks developing and focus-group testing various slogans or campaign ideas, a team can generate dozens of variants of ad copy, images, or *customer journeys* within hours and at least qualitatively sound out what might be interesting. Of course, this does not replace market research, but it accelerates the idea-preliminary stage. Especially in agile marketing teams, something like "rapid prototyping of marketing ideas" becomes possible.

Furthermore, behavioral economics strategies can be more easily explored with AI: A marketer can, for example, use the AI to generate various *nudges* for a desired behavioral change (e.g., more newsletter subscriptions)—from social proof formulations ("5,000 customers already use...") to scarcity appeals ("Only 3 spots left!") to *loss aversion* frames ("Don't miss out...").
These principles of behavioral economics, made popular by Thaler & Sunstein (2008/2021), can be creatively implemented with AI. One gives, for example, the instruction: "*Create 5 variants of a product banner, each based on a different psychological principle (scarcity, social proof, authority, ...).* " The results provide a quick overview of how different approaches might look. This would be extremely time-consuming manually.

Another area is the scaling of standard communication: Companies often have recurring communication types—answering customer inquiries, press releases, internal newsletters, onboarding documents. With well-designed prompts, one can create templates here that save considerable time. Example: A personnel department develops a prompt that formulates an appealing, diversity-conscious job ad from job description bullet points. Or a sales team has a prompt that automatically generates a personalized offer email from CRM notes, but in the company-specific tonality.

Such **prompt libraries** become the valuable intellectual capital of an organization. For they contain condensed know-how: How do we speak as a brand? What do we need to pay attention to (e.g., no discriminatory language)? Which arguments work with which customer group? Every good prompt encapsulates such experiences. When employees share them, a **knowledge management effect** is created: The knowledge of individuals (e.g., of an experienced PR professional on how to get out of tricky questions positively) can be made available organization-wide via prompts.

One could imagine "Prompt Styleguides" in the near future, analogous to corporate language manuals. It would say, for example: "*For social media posts, always use a role pattern 'you are an enthusiastic customer who loves our product XY', avoid jargon, max. 2 emojis.*" Such guidelines could be directly cast into prompts or serve as instructions for employees who produce text with AI. Companies are already experimenting with anchoring *brand personas* in LLMs so that answers match the brand image.

Internal knowledge transfer can also benefit: An employee could, via prompt, consult a "virtual mentor" who gives advice based on company knowledge (provided the AI has been fed with the corresponding internal documents and data protection is sufficiently ensured). Such an AI could onboard new colleagues faster by answering routine questions ("How do I submit a vacation request?") or explaining complex processes. It is important here that the prompts are well-maintained so that the AI provides consistent and correct information—here the topic of knowledge management comes into play again: The quality of the AI's information is only as good as the curated inputs and prompts.

Exemplary: Imagine a company that maintains a prompt repository—each department contributes its best prompts.

- In marketing, for example: a "*Launch-Plan Checklist*" prompt (AI lists all necessary tasks),
- in HR: a "*Prepare for a difficult employee conversation*" prompt (AI simulates the employee's answers to various communication styles),
- in customer service: an "*Answer generator for complaints*" (Input: bullet points on the case, Output: a ready-formulated friendly letter incl. a goodwill offer).

These prompts would be reviewed, legally approved, and constantly adapted to new findings. The company would thus have a kind of prompt asset that provides it with productivity—employees do not have to reinvent the wheel every time but use proven AI dialogues. This, of course, presupposes that such content is continuously updated (e.g., when the company policy changes)—a new aspect of knowledge management: Prompt Management.

It also raises questions of governance: Who is allowed to use which prompts? How does one prevent confidential information from flowing out via public AI queries? Clear guidelines are needed here, for example, that one uses company-internal LLMs or anonymizes sensitive data before the prompt.

An interesting special field is internal change communication: In the case of a major restructuring, for example, managers could use AI to formulate coherent messages. At the same time, one could also use the AI to anticipate how employees will react—e.g., "*Play an angry employee: what are his main points of criticism about the restructuring?*"—to prepare for it. Thus, AI becomes a communication trainer.

Example 22: AI-supported FAQ in employee communication. An HR team is introducing a new home office policy. They expect many questions from the staff. Instead of answering them manually one by one, they proactively create an FAQ document with AI help.
The prompt: *"You are an HR manager. List 10 common questions (and suitable answers) that employees are likely to ask about the new home office policy. Pay particular attention to concerns about overtime, insurance, ergonomics, and team meetings."*
– **Result:** The AI delivers, for example: "Q: Do I have to document overtime differently in the home office? A: ..."; "Q: Who pays for the equipment (chair, screen)? A: ..."; "Q: How do we ensure that team spirit does not suffer? A: ..." etc.

The HR team checks and adapts the answers (expert knowledge is needed here; the AI's answers are generic but must comply with company rules) and sends out the FAQ together with the policy announcement.

Commentary: Through the AI-supported perspective shift (the AI "thinks" like an employee with possible concerns), the team was able to communicate preventively and show that it takes employee perspectives seriously. This improves the acceptance of the measure. Something similar could be done with external customer FAQs or press pitches ("What critical questions might journalists ask?"). Thus, AI becomes part of issue management.

In sum, one can say: Structured prompting in organizations enables faster cycles (idea → draft → feedback), cost-effective tests of messages or concepts, and a certain standardization of knowledge work. Well-crafted prompt libraries and guidelines become a central component of organizational knowledge management. Companies that adapt this early could have a competitive advantage because they use collective expert knowledge more effectively. However, one must also bring the employees along: It is important to offer training (many employees may have fears of contact or unrealistic expectations). Here the circle closes to education: University graduates who bring "Prompt Literacy" with them will be in high demand.

Research, too, can benefit from prompt engineering, especially through the possibility of conducting simulations that would be difficult to implement in reality. In social and economic sciences, for example, complex experiments are often expensive, ethically delicate, or logistically demanding.

Prompt-based simulations allow testing hypotheses *in-silico*. Park et al. (2023), for example, have shown that one can simulate an entire small town with LLM agents, in which the virtual inhabitants show believable social interactions.
Such *Generative Agents* open new horizons: One could simulate political science scenarios (e.g., the diffusion of rumors in social networks) by giving AI agents corresponding roles and then observing what happens. Or in economics, model market behavior by having many AI agents act as sellers and buyers and react to price signals. Of course, these simulations do not replace real experiments—the risk of failure is there if the AI does not truly map human psychology. But they can serve as preliminary studies: to explore parameters, generate hypotheses, and sound out the limits of a model before one embarks on more elaborate empirical projects.

In the field of psychology, one could experiment: e.g., use an AI as a virtual subject to see how different formulations of a survey are understood. Or as a virtual therapist to test therapy techniques in a controlled setting (with caution, of course). In the natural sciences, LLMs can help to summarize research literature or to hypothesize what might come out of certain experiments—here they are more like assistants in the theory-building process.

A particularly exciting field is methodology research: One can use AI to test new research methods. For example, the concept of "*AI in the Loop*" studies: Human subjects + AI generate solutions together, and one examines this interplay experimentally. Something like this was science fiction a few years ago, now it is feasible.

Qualitatively, too, LLMs can serve as idea generators. Researchers can use them to draft counter-positions or critical comments. A scientist could, for example, give their own paper draft to the AI and say: "Find all possible points of criticism or weaknesses in my argumentation." The AI will surely find something—perhaps also incorrect things—but that forces the researcher to be more robustly prepared. So one has a kind of digital reviewer. This can increase the quality of work before it goes into peer review.

As in all fields of application, common sense and responsibility are needed here too. Especially in research, AI must not be taken as an oracle—it is known to hallucinate sources or facts. Prompt outputs must therefore be rigorously checked. But they can enrich the inspiration.

An advantage: The hurdles to trying out creative, outlandish ideas are lowered. Research processes could become more experimental because "failing" costs less effort—one types a prompt and gets an answer, and if it's junk, only a little time was lost. This promotes, in the best case, curiosity-driven exploration.

However, there is also the danger that AI will be too normalizing—because it is trained on existing knowledge, it could keep researchers on well-trodden paths. Caution is advised here: As a researcher, one should see AI as a partner but not submit too much to its search/answer mode. It is important to deliberately pose breakout prompts that may seem daring.

In summary: Prompt engineering offers science new methodological tools. Multi-agent simulations with LLMs allow for exploratory experiments that are realistically inaccessible. The ability to process enormous amounts of text (literature, data) via AI can increase the speed of research. And the role of AI as a discussion partner can enhance reflexive quality. Nevertheless, the human remains the hypothesis-generating and interpreting part—AI provides patterns and possibilities, but the classification must come from professional expertise.

Interestingly, the integration of AI into research forces one to deal with openness and reproducibility: Prompting is not always deterministic (the same prompt can give slightly different answers), so one may have to document prompts in publications so that others can replicate it. This could become the standard in the future (analogous to method descriptions today: one specifies parameters, one would then also have to specify the exact prompt and the model, etc.). This promotes transparency and could also foster the development of prompt reference collections for research purposes.

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9. Fazit

Good prompting is good thinking. The analysis presented here substantiates this leitmotif: The elaboration of sophisticated prompts goes far beyond merely issuing technical instructions. Rather, it is a **cognitive practice** that activates and trains central pillars of the human intellect:

The structured problem-solving of *Computational Thinking*, the flexibility of *Multi-Model Reasoning*, the methodological rigor of *Systematics*, the innovation engine of *Creativity*, and the boundary-crossing power of *Imagination*. Numerous case studies have illustrated how these abstract thought processes become concrete, applicable, and teachable through prompting. Prompt engineering thus proves to be more than a transient collection of tricks for dealing with chatbots—it is an emerging **meta-competence** of the digital knowledge society.

One could say that prompting is a new form of **cognitive literacy** in the age of AI. Just as reading and writing once became the foundation for storing and communicating complex thoughts, prompting allows us to use the **interaction with intelligent machines** as an extension of our thinking. Whoever masters this language of the machines can use them as an idea generator, dialogue partner, teacher, or simulation space—and thereby potentiate their own mental performance. Research, education, and professional communication can be sustainably transformed by this **human-AI collaboration**.

However, good prompting—like good thinking—requires practice, reflection, and contextual knowledge. It is not an automatism: A smart prompt arises from a clear problem definition, conscious methodology (paradigms, patterns), and critical evaluation of the results. In this respect, prompting also sharpens our awareness of the quality of questions and instructions. The old computer science saying "Garbage in, garbage out" proves true: Unclear input leads to nonsensical output. Conversely, a precise, well-thought-out prompt can bring forth astonishing things.

The future will show how this skill institutionalizes. Will we be teaching "Prompt Literacy" as a matter of course in a few years, just as we teach textual competence today? Will companies employ prompt engineers or award certificates in prompt design? Will scientific papers name AI co-authors who contributed via prompting? Platforms for sharing successful prompts are already emerging—*open-source thought scripts*, so to speak. This points to a cultural shift: Knowledge no longer manifests only in books or program codes, but also in cleverly formulated AI dialogues.

In a world where AI systems are becoming ubiquitous, the ability to steer these systems meaningfully is essential. Here, "steering" is not to be understood as one-sided control, but as interactive understanding: We must learn to think *with* the AI, not just let *it* think. Good prompting teaches us exactly that—it forces clarity in our own minds, anticipation of what the dialogue partner (the AI) needs, and iteration until satisfaction. All of these have been hallmarks of excellent human thinking for a long time.

In conclusion, it can be said: Prompt engineering is here to stay. As an interface between our creativity and the computing power of AI, it has the potential to fundamentally expand the way we solve problems, create knowledge, and communicate. In doing so, we should never forget that the prompt, while technically a piece of text, embodies a **mental**

act. When this act is performed consciously, skillfully, and reflectively, then it is indeed true: Good prompting is nothing other than good thinking—and it can help us to think even better.

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