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Mental integration with generative AI through computational thinking

Information Systems Science
Bachelor's thesis

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The rapid development of artificial intelligence (AI) has been received with both fear and excitement. The future of the field is clouded by uncertainty, inviting speculation of its direction. This thesis views the future as a path of collaboration, wherein humans and AI systems are working together, utilizing their respective strengths. While the collaborative path is not assured, it represents a balanced approach where humans retain a degree of control over AI.

As AI systems settle in societies, we are faced with the question: how can we best leverage their potential? To narrow down the question, this thesis focuses on generative AI systems. These systems are often built as user friendly interfaces that appeal for the general populace. Behind the seemingly simple interfaces lie numerous directions towards enhanced collaboration. These directions can be broadly categorized into two groups: (1) enhancing the knowledge of AI systems and (2) refining the AI systems themselves. This thesis attempts to provide guidance by bridging the gap in mutual understanding between the user and the generative AI system. The analysis is approached through computational thinking.

According to the results obtained, computational thinking is an integral tool for understanding AI. The relationship with computational thinking and human-AI collaboration is further explored by focusing on the four characteristics of computational thinking. The characteristics include problem decomposition, algorithmic thinking, abstraction, and automation. Each characteristic provides additional techniques for enhanced collaboration.

Further findings underline the importance of several prerequisites for efficient collaborative work. Explainable AI, mutual trust, and mutual understanding lay the foundation for collaboration with generative AI systems. As of now, opaque methods such as deep learning present challenges for explainability and mutual understanding.

Working with generative AI requires understanding when and how to utilize it. Allocating tasks according to the competencies of both the user and AI system highlights their complementary benefits. Using generative AI can be approached as a problem of finding the right abstractions through prompt engineering. Providing specific prompts that align with the semantics of the generative AI system promotes suitable outputs. Evaluating the output and giving feedback enables iterative improvement, as the AI system learns from its prior outputs.

Key words: human-AI collaboration, computational thinking, generative AI

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Tekoälyn nopea kehitys on herättänyt ihmisissä sekä pelkoa että innostusta. Alan tulevaisuutta ympäröi epävarmuus, joka on johtanut pohdintaan tekoälyn kehityssuunnasta. Tämä tutkielma lähestyy tulevaisuutta ihmisen ja tekoälyn yhteistyönä, jossa ihmiset ja tekoälyjärjestelmät hyödyntävät omia vahvuuksiaan. Yhteistyötä kuvaava tulevaisuus ei ole varmaa, mutta se edustaa polkua, jossa ihmiset ainakin osittain säilyttävät hallintansa tekoälyjärjestelmiin.

Kun tekoälyjärjestelmät asettuvat yhteiskuntiin, kohtaamme kysymyksen: miten voimme parhaiten hyödyntää niiden potentiaalia? Tarkempana rajauksena tässä tutkielmassa keskitytään generatiiviseen tekoälyyn. Generatiiviset tekoälyjärjestelmät rakennetaan usein käyttäjäystävällisiksi käyttöliittymiksi, jotka vetoavat laajaan yleisöön. Yksinkertaisten käyttöliittymien takana on kuitenkin lukuisia mahdollisuuksia parempaan ihmisen ja tekoälyn yhteistyöhön. Nämä mahdollisuudet voidaan jakaa yleisesti ottaen kahteen ryhmään: (1) tekoälyjärjestelmien ymmärtämisen parantamiseen ja (2) tekoälyjärjestelmien kehittämiseen. Tämä tutkielma pyrkii tarjoamaan ohjeistusta yhteistyötä varten kaventamalla keskinäisen ymmärryksen kuilua ihmisen ja tekoälyn välillä. Analyysin välineenä tutkielmassa käytetään laskennallista ajattelua.

Löydettyjen tulosten perusteella laskennallinen ajattelu on olennainen osa tekoälyn ymmärtämisen parantamista. Laskennallisen ajattelun vaikutusta ihmisen ja tekoälyn yhteistyöhön tutkitaan tarkemmin keskittymällä laskennallisen ajattelun neljään osa-alueeseen. Osa-alueet ovat ongelman hajottaminen, algoritminen ajattelu, abstraktio, sekä automaatio. Jokainen osa-alue tarjoaa täydentäviä käytäntöjä yhteistyön parantamiseksi.

Tutkimukset tuovat esiin edellytyksiä tehokkaalle yhteistyölle. Ihmisen ja generatiivisen tekoälyn yhteistyön perusedellytyksinä pidetään selitettävissä olevaa tekoälyä, keskinäistä luottamusta, sekä keskinäistä ymmärrystä. Toistaiseksi esimerkiksi syväoppimisen läpinäkymättömyys aiheuttaa haasteita perusedellytysten täyttymiselle.

Generatiivisen tekoälyn kanssa työskenteleminen edellyttää ymmärrystä siitä, miten ja milloin sitä käytetään. Tehtävät voidaan jakaa tekoälyjärjestelmien ja ihmisten kesken niiden osaamisalueiden mukaisesti. Tämä korostaa näiden täydentäviä osaamisalueita ja parantaa työn tehokkuutta. Generatiivisen tekoälyn käyttöä lähestytään syötteiden avulla, joiden suunnittelu muodostaa merkittävän rajapinnan ihmisen ja tekoälyn yhteistyölle. Yksityiskohtaiset, tekoälyjärjestelmän semantiikan kanssa yhteensopivat syötteet mahdollistavat merkityksellisen kommunikaation. Generatiivisen tekoälyn ulostulon arviointi sekä palautteen antaminen luovat pohjan iteratiiviselle kehittymiselle, kun tekoäly oppii aiemmista ulostuloistaan.

Avainsanat: ihmisen ja tekoälyn yhteistyö, laskennallinen ajattelu, generatiivinen tekoäly

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1 Introduction

The last few years have demonstrated a new surge of interest towards AI systems. The desire to imitate the human mind through computing has proven to be a worthwhile venture. These years have also shown that AI has surpassed humans in complex tasks (Jarrahi, 2018). Regardless of how user-friendly AI interfaces are created, their function inevitably concerns computational processes. While the field is rapidly moving forward, the understanding of these underlying processes through computational thinking remains an essential competency (Celik, 2023; Grover & Pea, 2017).

The future course of AI development remains uncertain. Speculation of its direction can be categorized into three prospects. First, AI will outperform humankind in all areas, erasing the need for human efforts. Second, AI will not be able to surpass humans in social aspects, claiming that human intelligence cannot be entirely replicated with AI. Third, a superior intelligence lies in the cooperation between humans and AI systems, forming a collaborative human-AI society. (Peeters et al., 2021.) As we navigate an era where collaboration between humans and machines could become increasingly prevalent, examining how computational thinking serves as a bridge between human cognition and AI systems is central. This thesis explores the path of human-AI collaboration by focusing on three relevant research questions.

Research questions:

1. How does computational thinking contribute to the collaboration between humans and generative AI systems?

2. What are the requirements for seamless Human-AI collaboration?

3. How to effectively utilize generative AI systems in practice?

This study is carried out as a literature review. The findings from existing literature are compared and analysed further, focusing on effective human-AI collaboration. Collaborative work with AI is a trending topic, which is reflected in the academic literature. Utilizing the quickly developing AI tools is approached from different perspectives, and this thesis will view the collaboration through computational thinking. Research on computational thinking often focuses on school education (see, e.g. Grover & Pea, 2013; Lee et al., 2011; Weintrop et al., 2016), which may not always be generalized to other domains. Connection between computational thinking and generative AI has an academic foundation but remains relatively unexplored. Building on this foundation, this thesis reviews closely related academic literature and aims to provide a generalized approach towards collaboration with generative AI systems.

This thesis has been written with partial assistance from ChatGPT, a widely recognized generative AI system by OpenAI. The system is utilized as an assistant in sentence construction, producing different approaches to the same contextual semantics. All AI provided information is revised and modified accordingly.

The analysis covers human-AI collaboration but is limited by the approach of computational thinking and generative AI. Technical complexity is minimal, reflecting the level of understanding needed to effectively utilize generative AI systems. The aim is to offer universally applicable results relevant to anyone working with generative AI.

The approach to the subject begins from Chapter 2, which introduces the concepts of computational thinking, human-AI collaboration, and generative AI. It discusses the definitions of each concept and their relationship with each other. Chapter 3 views collaborative work with generative AI through the individual characteristics of computational thinking. The chapter is divided into four subchapters, which are problem decomposition, algorithmic thinking, abstraction, and automation. These subchapters dive deeper into the intricacies of human-AI collaboration, aiming to provide further theoretical background for the research questions. Chapter 4 summarizes and discusses the observations made in this thesis, clarifying the results to the three research questions.

2 Computational thinking and human-AI collaboration

2.1 Computational thinking

The definitions of computational thinking vary based on technicality. Some consider it solely problem-solving, while others define it strictly as an approach to the field of computer science. Wing (2010) suggested that “Computational thinking is the thought processes involved in formulating problems and their solutions so that the solutions are represented in a form that can be effectively carried out by an information-processing agent”. In other words, it refers to the ability to approach problems and tasks by leveraging principles fundamental to computer science. This thesis applies computational thinking by this definition, which reflects computer science and emphasizes problem-solving.

Viewing computational thinking as a competency allows for a closer inspection of its utilization on a personal level. It is inherently an intangible asset that has the potential to significantly enhance problem-solving capabilities, although often remaining implicit as tacit knowledge (Tedre & Denning, 2016). The tacit nature of computational thinking means that it is embedded within the cognitive processes of individuals, making it difficult to articulate. For the same reason individuals may possess computational thinking skills without being aware of it, making it essential to recognize and cultivate these abilities.

Computational thinking can be categorized into four main characteristics, which include problem decomposition, algorithmic thinking, abstraction, and automation (Yadav et al., 2017). These are derived attributes from the field of computer science, highlighting the approach to solve problems in a structured- and analytical manner. By breaking down the concept of computational thinking into smaller characteristics, we can examine its attributes more thoroughly. The individual characteristics will be further explored in Chapter 3.

2.2 Generative AI

Artificial intelligence is a broad term used to describe the systems that imitate human intelligence. To maintain a more specific focus, this thesis will specifically focus on generative AI. “[Generative AI] refers to computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data" (Feuerriegel et al., 2024). Generating new content is possible through the examples and correlations from the training data. This process is called machine learning.

Machine learning can be categorized into three main types, which are supervised learning, unsupervised learning, and reinforcement learning. Supervised learning involves providing the AI system with examples consisting of inputs along with their corresponding desired outputs. By doing so, the system learns to recognize patterns and correlations within the data, enabling it to make predictions based on these learned relationships. Unsupervised learning, on the other hand, provides the input data without their corresponding outputs. Instead, the system autonomously discerns patterns and structures within the data. Lastly, reinforcement learning is an inherently different learning method, where the AI is learning from feedback based on its actions. The system learns to achieve its goals with the objective of maximizing its positive feedback rewards. (Jordan & Mitchell, 2015.) Figure 1 below illustrates a simplified generative AI system that reflects these findings.

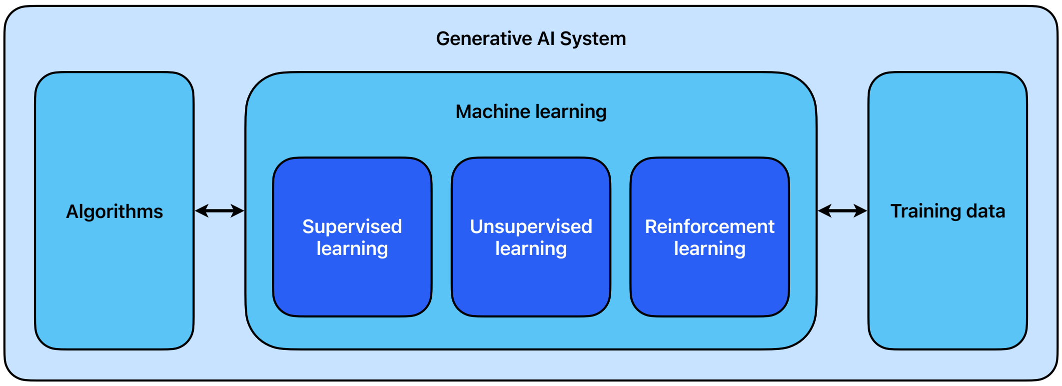

Figure 1 Machine learning with generative AI

The figure displays a simple machine learning structure that can be implemented within generative AI. This structure is characterised by the relations between algorithms, machine learning and training data (Feuerriegel et al., 2024). The relations convey the role of machine learning methods, which serve as a bridge between training data and algorithms.

Supervised learning, unsupervised learning and reinforcement learning are integral for machine learning. However, they alone do not capture the complexity and capabilities of modern machine learning techniques. Deep learning leverages these learning methods by utilizing multi-layered neural networks (Jordan & Mitchell, 2015). Similarly to neurons in biological brains, artificial neural networks process information through interconnected nodes. These nodes are connected as layers, where each layer is refining the information further. Deep learning follows this architecture by leveraging multiple hidden layers. (Fazi, 2021.) Figure 2 represents a scalable artificial neural network.

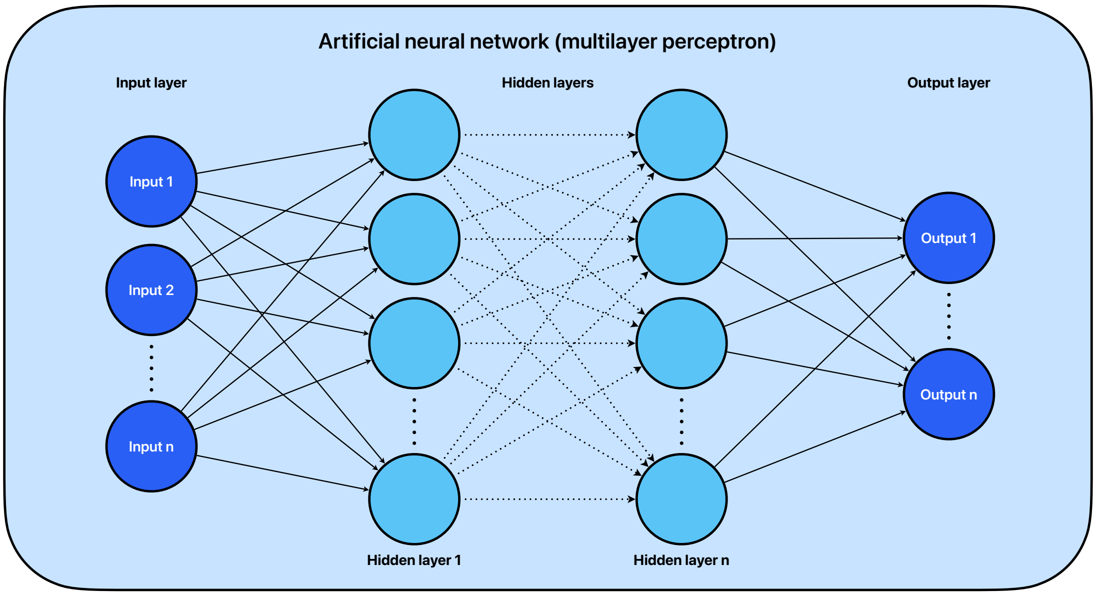

Figure 2 Artificial neural network, multilayer perceptron (adapted from Sarker, 2021)

The process of applying neural networks can be approached through different algorithms. The model represented in Figure 2 is called the multilayer perceptron. Its usage begins from the input layer, which is connected to all the nodes of the first hidden layer. All the nodes of the first hidden layer are then connected to all the nodes of the second layer, and so on. The last hidden layer connects to the output layer, which provides the output of the process. (Sarker, 2021.)

Despite their remarkable capabilities, modern deep learning programs have become so complex that even their developers find it challenging to comprehend them fully. Due to the opaque nature of deep learning, these programs are often referred to as black boxes.

The interaction with black boxes consists of providing inputs and receiving outputs, managed by an unknown process. (Fazi, 2021.)

2.3 Human-AI collaboration

Human- and artificial intelligence (AI) have fundamental differences. The two differently structured intelligent entities differ in speed, connectivity, updatability, scalability, energy consumption, and basic structure (Korteling et al., 2021). Based on the existence of such fundamental differences, it becomes evident that collaborative effort could provide significant benefits in leveraging the strengths of each intelligence type.

There is a growing concern regarding the potential for AI to surpass humans across all domains in the future and label human work obsolete. The concern is not irrational, since AI is proving to be able to complete an increasing number of tasks previously requiring human intelligence. An alternative vision for the future of AI is collaborative work, wherein humans and AI leverage their respective strengths. (Jarrahi, 2018.) Human-AI collaboration is a phrase used to characterize the interaction between humans and artificial intelligence as they cooperate on tasks and exchange information (Hong et al., 2021). While it is not certain that human-AI collaboration is going to be the overarching future in AI, it represents a path where humans keep a degree of control to themselves.

The broad nature of generative AI systems allows them to be applied across various domains. As an example, consider the field of art. Creating art in collaboration with generative AI allows for the exploration of new creative possibilities by combining human ideas with AI-generated elements. Collaborative art projects can provide new perspectives for the artist and result in better outcomes. Hitsuwari et al. (2023) demonstrated this through a survey where haiku poetry was evaluated by 385 participants based on 21 different metrics such as beauty. The survey found that haiku poetry which was written in collaboration with AI was considered superior compared to those crafted solely by humans or AI alone. This result ties well with research from Hong et al. (2021), where the significance of human-AI collaboration is covered more broadly from a teaching perspective. While the potential advantages of collaboration appear promising, there are still numerous challenges in realizing them.

One of the barriers to collaboration between humans and AI is the comprehension of AI systems. For the collaboration to be efficient, the user must comprehend the AI's output and often the process behind it. In other words, AI should be explainable in order to achieve seamless human-AI collaboration. Explainable AI refers to the capability of AI systems to be understood and interpreted by humans (Hong et al., 2021.) Lack of comprehension regarding the reasoning behind the output could result in asymmetrical understanding between the participating agents, thereby undermining the efficiency of the collaborative effort.

In addition to mutual understanding, building trust is also essential for effective collaboration between human intelligence and AI (Feuerriegel et al., 2024; He et al., 2023). According to Vössing et al. (2022), users develop trust in AI systems when they provide reasoning for their output, while trust decreases when the output is based on uncertain sources. These findings support the notion that trust is built upon transparency and reliability in both directions. Users need to trust that the AI's output is accurate, while AI systems should be explainable for users to understand their decision-making processes.

The black-box nature of modern generative AI systems poses difficulties for both directions. The opaque deep learning systems are not fully explainable and make it difficult for users to understand the reasoning behind the outputs. Considering the lack of transparency, these systems require more trust from the users towards the reliability of AI generated outputs. (Feuerriegel et al., 2024.)

2.4 Integrating computational thinking into human-AI collaboration

Technologies are constantly tailored better for the general populace. The usage of technologies is made easy, but learning to efficiently utilize them can require immense effort. While importance of emerging technologies such as AI is increasing, the competence to effectively work with them is becoming a necessary skill (Wang et al., 2023). Celik (2023) highlights the pivotal role of computational thinking in shaping an individual's AI proficiency. His analysis provides evidence for computational thinking contributing to the utilization, identification, and assessment of AI-driven technologies. Against this background, computational thinking could provide new avenues of competitive advantages by enabling innovative problem-solving approaches and enhancing decision-making processes.

Enhancing collaboration with generative AI systems can be categorized in two distinct paths. Firstly, improving the understanding of AI. Effective collaboration between humans and AI requires users to possess knowledge and skills about AI (Celik, 2023). Secondly, improving the AI system itself. This could involve tasks such as enhancing explainability or refining the reliability of the systems (Feuerriegel et al., 2024). These two paths are explored further in Chapters 3 and 4.

From the perspective of developing AI systems, the importance of computational thinking can be summarized in three key points. These involve (1) improving AI through computational thinking, (2) enhancing AI with insights into human learning, and (3) ensuring AI systems are explainable. (Dohn et al., 2022.) This thesis will focus on the usage of AI and thus will not expand further on the role of computational thinking in its initial development. However, it is important to make two distinctions before moving forward. First, the user's ability to effectively use AI does not require them to be experts on the technical theory of AI systems (Wang et al., 2023). Second, the usage of AI is closely linked with its development through providing feedback on outputs and understanding the AI's basic functions behind its outputs (Vössing et al., 2022). These distinctions reflect on the relationship between AI systems and their users. While a thorough technical understanding is not required, the user's actions are affecting the development of AI.

3 Bridging human-AI differences for enhanced collaboration

Fostering the collaborative relationship with generative AI systems through computational thinking involves cultivating a mindset that embraces the four main characteristics of computational thinking. The characteristics include problem decomposition, algorithmic thinking, abstraction, and automation (Yadav et al., 2017). This chapter will delve into each characteristic, providing a comprehensive representation of the issue as well as techniques for enhanced collaboration with generative AI.

3.1 Problem decomposition

Central to computational thinking is the practice of breaking down problems into their sub-components, a process known as problem decomposition (Rich et al., 2019). It is based on the idea that the smaller sub-components are easier to solve than the original problem at once. This approach enables a clearer understanding and more effective resolution of the underlying problem by task simplification.

The findings from Denny et al. (2024) concerning work with generative AI systems suggest that when tasks are broken down for generative AI systems, it enhances the user's sense of clarity. Because understanding the task is necessary to explain it effectively, decomposing tasks for the AI requires a clear logic behind the prompts. This creates an enhanced environment for mutual understanding and reciprocal learning. An example of this could be prompting a generative AI system to segment a math problem into smaller, solvable equations. This way both the AI and its user are reaching for the same level of understanding.

In many ways, problem decomposition marks the starting point for human-AI collaboration. Decomposing complex problems into smaller parts may reveal sub-components that demand distinct skill sets to address. Allowing the allocation of the sub-components according to the competencies of both the user and AI system highlights their complementary benefits (Jarrahi, 2018; Vössing et al., 2022). When the task allocation is done, both the user and the AI system can start working on the problem sub-components. This enables generative AI to excel in computationally heavy tasks while utilizing the users' individual competencies. In other words, associating problem decomposition with human-AI collaboration emphasizes joint problem-solving, optimizing human expertise and AI capabilities. The competency-based allocation is also referred to as comparison allocation (Abbass, 2019).

The problem of allocating a task can be divided into static- and adaptive allocation methods. In addition to comparison allocation, other static allocation methods include leftover allocation and economic allocation. Leftover allocation aims to maximize the use of AI for as many tasks as possible, whereas economic allocation utilizes the most cost-effective way to maximize the benefits. (Abbass, 2019.) The appropriate method can be chosen based on the requirements of the situation.

Adaptive allocation proposes a different approach by including the temporal dimension. With adaptive allocation, the distribution of the task is changing dynamically according to the current specific needs. For example, in medical diagnosis, allocation between human doctors and AI systems could evolve over time, initially relying on human expertise and progressively incorporating AI assistance as data accumulates. This creates a need for an allocation agent that oversees the changes in allocation. The allocation agent could be a human or an AI. (Abbass, 2019.) Human allocation agents naturally rely on their individual knowledge and competencies, while AI-based allocation agents could leverage the wide array of data available to them. Considering the emphasis of this thesis on effective human-AI collaboration, the focus will be on comparison allocation and adaptive allocation methods.

3.2 Algorithmic thinking

Algorithms are systematic step-by-step procedures designed to achieve a specific objective or to solve a problem (Grover & Pea, 2017). Incorporating structured collaborative problem-solving extends beyond problem decomposition by breaking down the task into its sub-components and addressing them methodically through an algorithmic approach. Part of the algorithmic approach can be assigned to iterative improvement of both parties. According to Vössing et al. (2022), humans can not only enhance their learning through AI-generated output but also leverage their expertise to refine the AI system itself. This underlines that by understanding the AI provided output, we can establish feedback loops that maintain human involvement in the advancement of AI. An example of this concept might involve using a simple thumbs-up for suitable outputs and a thumbs-down for other ones. This way, the AI system can use the previous output as learning data, improving its overall performance.

Viewing problems as algorithms solvable through a set of instructions enables computational solutions. As an example, the problem of sorting a list of numbers in ascending order could be solved through the following simplified algorithm:

1. Start at the beginning of the list.
2. Compare adjacent elements [n1, n2] in the list.
3. If n1 > n2, swap them.
4. Inspect the next element and repeat steps 2 and 3 until no more swaps are needed.

This algorithm takes any list of numbers and systematically sorts the list. The example resembles pseudocode, which is general code independent of any programming language. Approaching computational thinking through programming is an effective learning method (Celik, 2023; Grover & Pea, 2017). However, generative AI has recently refined its problem-solving with natural language, diverting humans from the task of traditional algorithmic thinking to some extent. Collaboration with models capable of interpreting natural language calls for different means of algorithmic thinking. The focus then shifts from translating the problem into a format understandable by the computer to understanding how the computer processes the problem and evaluating its output. (Denny et al., 2024.) By getting a basic understanding of the underlying AI system, we can engineer specific prompts to get the most effective outputs.

The literature on prompt engineering is still relatively young, so new discoveries are frequent. White et al. (2023) define prompt engineering as the means by which large language models (LLMs) are programmed via prompts. LLMs are a subset of generative AI, specifically concentrated on modelling and generating text (Feuerriegel et al., 2024). In line with this view, Liu and Chilton (2023) offer a similar definition, describing prompt engineering as “the formal search for prompts that retrieve desired outcomes from language models”.

As defined in Chapter 1, computational thinking involves devising problems and solutions in a manner that an information-processing agent can effectively execute (Wing, 2010). In this context, the information-processing agent is a generative AI system, and prompt engineering is the act of computational thinking. Interacting with generative AI systems currently entails providing prompts, which serve as instructions or cues to the system, leading to content creation based on these prompts (Feuerriegel et al., 2024). Viewing this through the importance of computational thinking skills in AI collaboration (Celik, 2023.), it becomes clear that prompt engineering plays a crucial role in effectively utilizing generative AI.

A key challenge in prompt engineering is ensuring that the prompts align with the semantics of the generative AI system, which are derived from its training data (Vartiainen et al., 2023). In other words, making sure the prompts match the way the AI system was trained to understand language. This is an important challenge, because the better the prompts given by the user, the better the quality of the generated output will be (White et al., 2023).

The methods for prompting can be divided into different prompt categories that enhance communication and interaction. These categories guide the exchange of information, error identification, context control, and prompt improvement. (White et al., 2023.) Table 2 below presents these main prompt categories with their corresponding prompt examples.

Table 1 Prompt categories with examples (adapted from White et al., 2023)

Prompt category	Prompt example(s)
Input semantics	*“By 'A', I’m referring to 'B'.”*
Output customization	*“From now on, provide outputs as if you were a high school teacher.”* *“Concatenate each output with the previous one”*
Error identification	*“Starting now, explain the process by which you arrived at your output.”*
Prompt improvement	*“Suggest an alternative approach to my question while maintaining the same context.”* *“If you can’t provide an answer, suggest similar rephrased prompts that you could answer”*
Interaction	*“Ask me questions about the conversation so far.”*
Context control	*“In your next outputs, focus on the project budget and disregard the timeline.”*

Understanding the different use cases for various kinds of prompts offers tools to promote effective human-AI collaboration. Input semantics and context control focus on refining the understanding and translation of user input. They enable users to provide context or clarify terms within their prompts, facilitating more accurate responses.

Output customization extends this concept further, allowing users to dictate the format, style, and even persona of the generated outputs. By specifying preferences such as the tone or structure of responses, users can ensure outputs align with their intended purpose or audience. (White et al., 2023.)

One of the unique challenges of utilizing generative AI lies in their variability. Unlike traditional tools such as compilers, LLMs can produce different outputs for identical prompts, some of which may be syntactically or semantically incorrect. This highlights the importance of critical evaluation of the generated output. (Denny et al., 2024.) The process of evaluation can be developed further with error identification by requiring the output to provide reasoning or relevant facts. While the final evaluative task is still with the user, a better understanding of the output allows them to make more informed decisions. Finally, prompt improvement and interaction highlight the collaborative approach to prompt engineering. For instance, collaboration can involve prompts aimed at refining questions or prompting the AI to inquire directly from the user. (White et al., 2023.)

Breaking down the task of prompt engineering into categories is utilizing the characteristic of problem decomposition. After decomposing the task, we can begin addressing it algorithmically through a step-by-step procedure. To collaboratively solve the previous example of sorting a list in ascending order, we can apply several prompt engineering categories. Input semantics could clarify that the list is to be sorted numerically. Then we have the option to customize the output by asking for a specific format, or implementation to a text. Error identification could prevent future mistakes by providing the process behind the outputs. Limiting the context to a specific sorting algorithm such as bubble sort could also be useful for evaluating the output. The sorting problem could now be solved as follows:

1. Input prompt: "*Sort the following list of numbers numerically in an ascending order using bubble sort: [n1, n2, n3…]. Explain the process behind your output.*"
2. Evaluate the output.
3. If necessary, refine the prompt collaboratively by asking for prompt improvements.

Even when following a structured approach with prompt engineering, suitable results are not always guaranteed. When working with generative AI systems, the user should understand their limitations. These limitations are mostly computational, concerning training data and the underlying algorithms (Feuerriegel et al., 2024). Because of the computational nature of the limitations, we can utilize computational thinking in working with them. More specifically, in this case we can use prompt engineering to refine the result. By understanding where the limitations come from, the user can make a critical evaluation of the provided outputs.

Effective prompt engineering aims to get around the main issues with generative AI by understanding them. These issues include ambiguity, overfitting, bias, lack of context, ethical considerations, unintended side effects, and unrealistic dependency on model limitations. (Giray, 2023.)

When providing instructions to a generative AI system, it is important to acknowledge the possibility of misinterpretations. Engineering a prompt requires clarity about the context of the task by focusing on explicit statements (White et al., 2023). The model may misinterpret the prompt if it contains ambiguous wording. In the current sorting example, the AI system could mistake the numerical values for text and try to sort them alphabetically. The opposite problem to ambiguity is overfitting, where the prompt is overly precise. This can also lead to misinterpretations through limiting the AI’s scope for outputs (Giray, 2023). Other unintended misinterpretations, such as assumptions based on previous context of the dialogue, may interrupt the coherence of the conversation (White et al., 2023).

Another potential issue is bias. The AI provided output reflects its training data, which has bias towards its learned patterns and correlations (Feuerriegel et al., 2024). This issue stems from the scale and quality of the model’s training data. An example of this is data imbalances. Machine learning may struggle to detect patterns in less frequent occurrences from the data, particularly with rare events. This could mean that data from important events such as rare diseases or minority rights get overshadowed by the majority of the dataset. In other words, the model may have a bias towards predominant data. (Batista et al., 2004.) This is another reason why users should not give unrealistic expectations for the generative AI systems but should rather critically evaluate their output.

3.3 Abstraction

Widely regarded as the keystone of computer science, abstraction is a characteristic that is also related to other computational thinking processes. It is a broad term used to describe generalization of information from one object to another, or simplifying complexity through hiding unnecessary details. (Grover & Pea, 2017.) In essence, anything that is not specified in full detail is an abstraction. An example of abstraction could be a map. Because it would be impossible to show every detail of the world in a single map, one must make decisions about which parameters to include. Is it a weather map or a road map? Do you need to know the elevation or the population density? A map is an abstraction that reveals only the chosen details of the world. From this standpoint, abstractions can be considered a necessary tool for communicating the world around us.

Abstraction also plays an integral role in human-AI collaboration. Communicating with computers through abstractions such as operating systems or programming languages has allowed us to partially hide their complexity (Grover & Pea, 2017; Klumbytė & Britton, 2020). The ability of AI to effectively process natural language brings the abstractions even further towards natural human functions. Communicating effectively with generative AI is also dependent on the prompts of the user (White et al., 2023). This implies that the abstractions made in prompt engineering must be interpreted consistently by the AI system. In essence, working with generative AI requires a mutual understanding of the abstractions. Since LLMs are usually trained with natural human language from sources such as books and websites, the AI learns to interpret words and grammar (Giray, 2023). However, as discussed earlier, there are still several issues with prompting the generative AI system (Batista et al., 2004; Feuerriegel et al., 2024; Giray, 2023; White et al., 2023).

Systems are built on top of abstraction layers, which serve a distinct purpose of simplifying the system for the end user (Wing, 2010). Based on the findings discussed in this chapter, Figure 3 below illustrates a simple model for the layers of abstraction when working with a generative AI system. The end user does not have to build the abstractions themselves, but benefits from understanding them through the ability to interpret the outputs and engineer effective prompts.

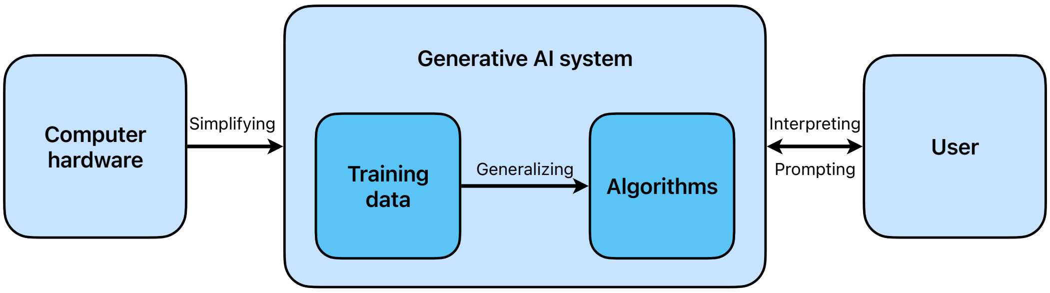

Figure 3 Layers of abstraction in collaboration with generative AI

As shown in Figure 3 above, creating abstractions is essential not only for humans but also for generative AI systems themselves (Fazi, 2021). Creating seemingly new information based on the generalizations from the training data is an abstraction itself. Reflecting on the previous analysis, abstractions are also essential in the communication between the user and the generative AI system. This layer is characterised by the language in their interaction. Fazi (2021) refers to the differences in human- and computer abstractions as “incommensurability”. This implies that the comparison between the two is not feasible due to the absence of a shared standard for assessment. Based on these differences, she takes on discussions about explainable AI. She mentions the main problem of explainable AI to be that AI is not currently providing clear explanations of its workings. The opaque nature of modern generative AI systems proves the emphasis on explainable AI reported by Dohn et al. (2022) and Hong et al. (2021) difficult to implement in practice.

3.4 Automation

Expanding on the previous chapter, automation is putting the abstractions into practice by executing them with a machine. In computational thinking, this means knowing what abstractions to make and when their automation is needed. (Grover & Pea, 2017.) Building on this idea, automation could be tied in with human-AI collaboration as the process of utilizing AI systems when needed, with the suitable prompts. This is in line with the analysis from Vössing et al. (2022), where they emphasized the idea of utilizing the differing competencies of the user and the AI system. Vartiainen et al. (2023) experiment with this idea by examining how students utilize generative AI tools in a design process. Their results lead to similar conclusions of distributed decision-making between the users and the AI.

The results of the analysis conducted by Vartiainen et al. (2023) are illustrated by a model of collaborative work with generative AI. The model describes the collaboration with four key stages, which are forming ideas, prompting, evaluation, and iteration. This framework is consistent with the findings discussed earlier but stands out as the first one to put them all together.

4 Discussion and conclusions

This thesis aimed to analyse the contribution of computational thinking to human-AI collaboration through relevant academic literature. The analysis was conducted as a review and synthesis of existing literature on the topic. The first research question was to examine the effect of computational thinking to the collaboration between humans and generative AI systems. This is a broad question that was discussed in detail throughout Chapter 3. The findings demonstrated that computational thinking is an integral tool for understanding and working with AI (Celik, 2023). Further exploration of the human-AI collaboration was done by focusing on the four characteristics of computational thinking listed in Table 2.

Table 2 Computational thinking characteristics in human-AI collaboration

Computational Thinking Characteristic	Integration with Human-AI Collaboration	Outcome
Problem decomposition	Breaking down problems into their sub-components	Enhanced clarity
	Allocation of task sub-components	Complementary benefits
Algorithmic thinking	Prompt engineering	Improved AI outputs
	Feedback loops	Iterative AI improvement
Abstraction	Simplifying computational complexity through AI interface	Simplified interaction
	Using mutually understood language	Effective communication
Automation	Knowing when and how to utilize AI	Task optimization

Table 2 presents the main discoveries around the first research question. It summarizes the outcomes of the integration of computational thinking characteristics with human-AI collaboration. First, problem decomposition allows for enhanced clarity by breaking down the original problem into smaller sub-components (Denny et al., 2024). These sub-components may require different competencies for addressing, revealing the complementary benefits between AI systems and their users (Jarrahi, 2018; Vössing et al., 2022). Second, the view of algorithmic thinking is changing from translating tasks to computers to understanding how the computer processes the problem and evaluating its output (Denny et al., 2024). This brings up new challenges such as prompt engineering and iterative improvement. In essence, prompt engineering aims to improve the AI's output by asking more suitable prompts, and iterative improvement utilizes user feedback to guide the AI system on what is a good output. Third, making abstractions in the form of a mutually understood language is a key challenge for collaboration with generative AI (Vartiainen et al., 2023). Improved understanding naturally results in more effective communication. Abstractions are also inherent in the computers themselves, since they are simplifying the complexity of the underlying computational processes (Wing, 2010). Fourth, in the context of human-AI collaboration, automation simply refers to the usage of AI. The key challenge in automation is knowing when and how to utilize AI (Grover & Pea, 2017).

The second research question concerns the requirements for seamless Human-AI collaboration. Based on the analysis by Dohn et al. (2022) and Hong et al. (2021), the adoption of explainable AI is important in AI utilization as it enables the user to better understand the outputs generated by AI systems. Considering the black box nature of deep learning, achieving complete explainability in AI poses significant challenges (Fazi, 2021). Additionally, He et al. (2023) and Vössing et al. (2022) emphasize the requirement of trusting the AI systems, which allows for proper reliance on their functionalities. As communication takes effect through abstractions made in language, a mutual understanding of the abstractions is also essential. This is reflected in prompt engineering, where the aim is to make sure that the AI system can correctly process the user's inputs (Giray, 2023; Vartiainen et al., 2023). In essence, seamless collaborative work between humans and generative AI systems requires three key elements: explainable AI, mutual trust, and mutual understanding. These requirements ensure transparency and reliability in the interaction, exposing an environment for effective collaboration. While essential for seamless collaboration, they should not be viewed as mandatory for any collaboration. Instead, these requirements should be regarded as areas for improvement.

The third research question focused on practical utilization of generative AI systems. Outlining the key findings of integrating computational thinking into human-AI collaboration, I provide a model for working efficiently with generative AI systems. The model offers a practical framework by breaking down the collaborative process into steps and guiding the progression through an algorithm. Figure 4 represents the proposed model for collaborative work with generative AI.

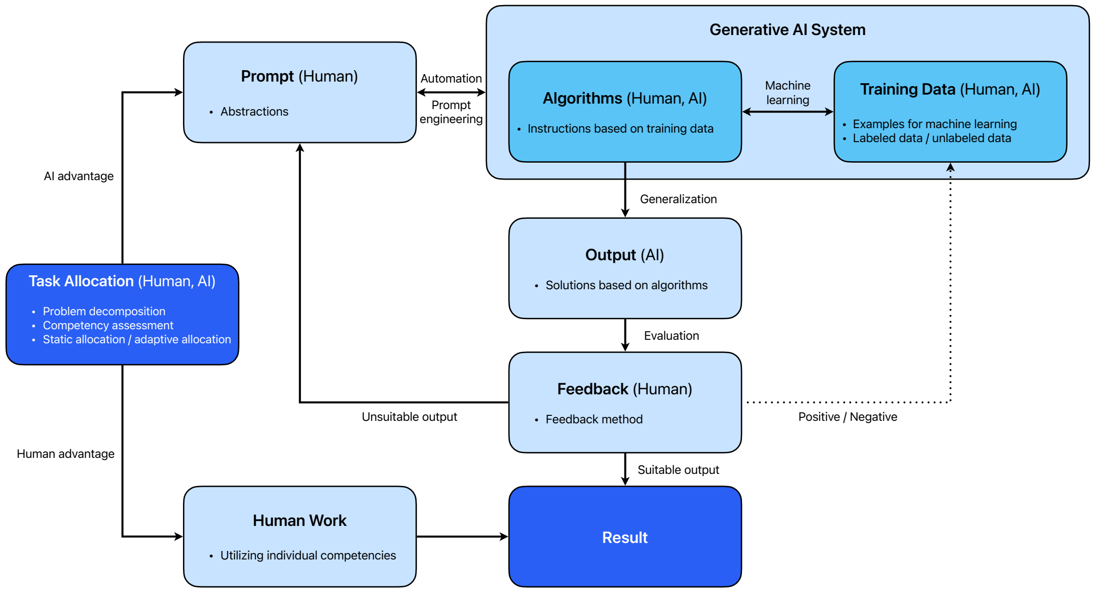

Figure 4 A model for collaborative work with generative AI

The model involves a structured approach aimed at maximizing the strengths of both humans and AI. The application of the model begins with task allocation. In this stage, the objective is to deconstruct tasks and split them into two pathways: one favouring human advantage and the other AI advantage. These paths are not mutually exclusive, but rather are happening simultaneously based on the competency assessment of the subtasks. Task allocation can be carried out by either a human or an AI system, and can include adaptive allocation or static allocation (Abbass, 2019).

In the human advantage path, humans take on problems that reflect their individual competencies. By focusing on tasks that play to their strengths, individuals can maximize their potential contribution to the collaborative effort (Jarrahi, 2018; Vössing et al., 2022). Individual human competencies have significant variations from person-to-person, which is why it is meaningless to provide a generalized framework for this path.

Under the AI advantage path, humans utilize prompt engineering to guide the generative AI system. Engineering a prompt requires abstractions that align with the semantics of the generative AI system (Vartiainen et al., 2023). Prompting provides outputs based on the learned patterns from the training data (Feuerriegel et al., 2024.), which are then evaluated by humans. Feedback guides adjustments, leading to iterative improvements of the system. In the case of unsuitable outputs, the user refines the prompts until suitable outcomes are achieved. (White et al., 2023.) This model harmonizes human creativity with AI capabilities for efficient collaboration and innovative results.

To put the model into practical context, consider a collaborative project where both human designers and generative AI work together on designing a new logo for a company. The task of designing the logo is broken down into sub-components and allocated by the advantages of both human and AI capabilities. With adaptive allocation, AI could be utilized based on the changing needs of the design process. Static allocation, on the other hand, could involve setting a solid plan to utilize AI only for producing different logo variations. For the purposes of this example, consider the latter.

Human designers then leverage their artistic skills and intuition to generate the initial ideas and sketches. The output of the human designers could consist of initial logo concepts that reflect their creativity and artistic vision. These outputs serve as the foundation for further refinement.

Simultaneously, AI algorithms are employed to assist in the logo design process. The proper questions are formulated with prompt engineering in collaboration with the generative AI. This may include prompts like "*Ask 10 questions to clarify the company's brand values*", and "*Suggest alternative logo concepts that incorporate elements from our brand identity guidelines*". The AI system then utilizes generative algorithms to produce logo variations based on the input provided. For example, AI algorithms could generate different font styles and colour combinations. Human designers evaluate the AI-generated logo variations, providing feedback on their relevance and alignment with the overall design direction. If the output is not suitable, the prompt must be refined through further prompt engineering.

The final logo design emerges through an iterative process of collaboration between human designers and AI algorithms. By breaking down the logo design task and leveraging the advantages of both human and AI capabilities, the collaborative team achieves an efficient approach to logo creation, ensuring the best possible outcome for the project.

This thesis covered the general relations between computational thinking and collaboration with generative AI. As a relatively new area of study, the lack of relevant literature challenges the provided results. The scope of this thesis remained relatively broad, opening opportunities for future research to explore specific areas in more depth. Especially prompt engineering appeared as a promising area of study as the tool between computational thinking and generative AI. The focus on collaborative optimization also left out broader ethical and societal challenges, such as the copyrights behind AI training data or the implications for the future job markets. Utilizing other interdisciplinary angles such as psychological, legal, and philosophical perspectives could take the analysis further.

A major limitation in the field of human-AI collaboration is the opaqueness of modern deep learning methods. This hinders the collaborative effort by making it more difficult for humans to understand the process behind the AI's output. (Hong et al., 2021.) While the results of this thesis rely on some level of mutual understanding between humans and AI systems, this is not a certainty in the future. The unpredictability surrounding the future of AI raises a question: If AI greatly surpasses human intelligence, can we even comprehend its reasoning anymore?

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