Agentic Relationship Dynamics in Human-AI Collaboration: A Study of Interactions with GPT-based agentic Information Systems Artifacts

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Abstract

Generative Artificial Intelligence (AI) having become increasingly embedded into work in both academia and industry has put a magnifying glass on Human-AI collaboration. With this paper we seek to answer calls for research on the interactions between human and AI agents and their outcomes. We adopt the Information Systems (IS) Delegation Framework (Baird & Maruping, 2021) to look at dynamics in relationships between human agents and Generative Pre-trained Transformer (GPT)-based agentic IS artefacts and how these dynamics manifest. By conducting and analyzing data from semi-structured interviews we were able to identify five salient agentic relationship dynamics affecting common understanding, willingness to delegate, cognitive load in human agents, confidence, and human agents' abilities to break GPT-based agentic IS artefacts' "thought loops". With this we aim to provide nuanced insight into GPT-based agentic IS artefacts and agentic relationship dynamics involving cognitive tasks.

Keywords: IS delegation, agentic IS artifacts, generative artificial intelligence, generative AI

1. Introduction

"The skills required in a world powered by ChatGPT and related technologies will be different" (Dwivedi et al., 2023, p. 4). A software developer with an artificial intelligence (AI) collaborator, in an AI-assisted software development scenario, can get work done twice as fast as one without (Kalliamvakou, 2022).

A common trait among chatbots such as ChatGPT is that they build on the Generative Pre-trained Transformer (GPT) architecture (Radford et al., 2018) that uses a combination of unsupervised learning and reinforcement learning from human feedback (Dwivedi et al., 2023) and works by attempting to predict the next token in a sequence of tokens such as sub-words and Unicode characters. By repeatedly predicting the next token (Radford et al., 2018), a GPT can generate new content. The result is a chatbot that responds to prompts with answers on a variety of topics and with varying degrees of accuracy (Dwivedi et al., 2023).

Generative AI can automate tasks that have, historically, required skill on part of humans (Else, 2023; Thorp, 2023), including tasks commonly assigned to students at universities, such as authoring essays. This has led to debate (Dwivedi et al., 2023) in academia on how to capture the upsides of the technology while managing potential risks of, for example, cheating and deceitful conduct in both education and research publishing.

Meanwhile, there is a growing literature aiming at conceptualizing and explaining the Human-AI collaboration scenario in terms of mechanisms related to delegation of tasks between human- and non-human agents. This literature (see e.g., Baird & Maruping, 2021; Fügener et al., 2022) emphasizes agency on part of the Information Systems (IS) artifact as opposed to only on part of humans.

Delegation has been studied in terms of the effect of metaknowledge's impact on delegation performance (Fügener et al., 2022). Furthermore, work is ongoing on extending the framework for IS delegation proposed by Baird & Maruping (2021) by expanding its focus of analysis to include agentic IS platforms (Ellinger et al., 2021). Research is also being done on delegation dynamics related to performance appraisals based on delegation outcomes impacting willingness to delegate (Liu et al., 2022). Research into IS delegation has been proposed in the area of financial robo-advisors (Zou & Lei, 2021) and into dynamics related to performance appraisals based on delegation outcomes impacting willingness to delegate (Liu et al., 2022). Furthermore, the concept of delegation is being approach from theoretical perspectives, such as work systems (Alter, 2022) and somatic IS artifacts (Lorenz & Recker, 2023).

With this paper we seek to answer the calls for research on Human-AI collaboration, and specifically on interactions between human agents and AI agents and their outcomes (Dwivedi et al., 2023). We aim to do this by viewing these interactions in terms of delegations as explained in the IS Delegation Framework by Baird & Maruping (2021), emphasizing the agentic relationship that arises and exploring the dynamics of this special relationship.

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Research is ongoing in this area (e.g., Slaughter & Chen, 2021), however research is lacking in regard to the new breed of GPT-based agentic IS artifacts that have emerged. Thus, to shed light on agentic relationship dynamics, involving foundational delegation mechanisms of the IS Delegation Framework, in human agent- and GPT-based agentic IS artifacts dyads we pose the following research question:

What are the salient delegation mechanisms for Human-AI collaboration scenarios involving Generative AI, and how do they manifest?

2. Generative Pre-trained Transformer-based Agentic IS artifacts

The primary feature distinguishing agentic IS artifacts from other IS artifacts, as described in the IS Delegation Framework (see Figure 1), is that agentic IS artifacts can assume and in some cases transfer rights to and responsibilities for task execution as delegated to them by a human agent (Baird & Maruping, 2021). Large Language Models (LLM) implemented using the GPT architecture (Vaswani et al., 2017) can, upon being prompted, execute such tasks.

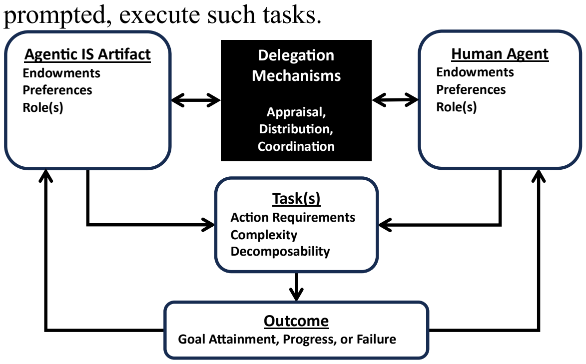

Figure 1. IS Delegation Framework (Baird & Maruping, 2021, p. 323)

For this, agentic IS artifacts are *endowed* with resource-based *assets* and *capabilities*. In the case of a GPT-based agentic IS artifact, a central asset is its vast training data. GPTs are not trained to perform a specific kind of task but are trained on large data sets containing data on a variety of topics and subject areas (Brown et al., 2020), and are then fine-tuned using Reinforcement Learning from Human Feedback to make the models generate more useful responses and to make them safer (Christiano et al., 2017). An example of model safety would be a GPT-based agentic IS artifact refusing to author a computer virus. The capabilities of the GPT-based agentic IS artifact thus arise out of the training process. GPT-based agentic IS artifacts possess what Baird & Maruping (2021) calls a complex decision-making model, which it uses to make decisions on task execution, that the GPT-based agentic IS artifact itself, even when prompted to, cannot give much insight into. This is in juxtaposition to a human agent's decision-making model which might involve intuition, emotions and in some cases a cost-benefit analysis (Baird & Maruping, 2021).

A human agent, such as a software developer, or a GPT-based agentic IS artifact, such as a chatbot, can occupy one or more of two roles: Delegator and proxy. The delegator transfers rights and responsibilities to the proxy, and the proxy accepts the transferred rights and responsibilities (Baird & Maruping, 2021). The transfer of rights and responsibilities is referred to as the *delegation* (Baird & Maruping, 2021) and is affected by several *delegation mechanisms*, namely *appraisal, distribution,* and *coordination.* An appraisal is an assessment of the other agent's endowments in the form of assets and capabilities and may be done emotionally or logically, and in relation to the endowments of the appraising agent, and can be subject to change over time as the relationship between the two agents develops (Baird & Maruping, 2021). Distribution is the mechanism by which rights and responsibilities are delegated and can happen via a straight transfer from one agent to the other, or via a negotiation and regulations in the forms of rules and constraints on task execution (Baird & Maruping, 2021).

After initial delegation, and thus after the agentic relationship has been established, *coordination* activities in the form of monitoring progress (Baird & Maruping, 2021) and updating regulations may be undertaken by either agent. Such coordination can incur costs on the agent doing the delegation (Baird & Maruping, 2021) in terms of, for example, time and attention. Integrative conditions for coordination relevant to delegation between a human agent and a GPT-based agentic IS artifact is *accountability, predictability and common understanding* (Baird & Maruping, 2021). When it comes to *accountability*, while a GPT-based agentic IS artifact can be delegated responsibility for executing a task, it is usually the human agent that is held ultimately responsible.

Predictability refers to "whether the agents understand the sequence of tasks and events and can apply this knowledge as a framework to future tasks" (Baird & Maruping, 2021, p. 329). Relevant for this condition is the tokenization of input and output by GPT-based agentic IS artifacts and their built-in token limitations. By design, ostensible for performance reasons, only a set number of tokens can be held in memory at a given time, which may impact predictability in some cases. Finally, *common understanding* refers to the knowledge shared between agents (Baird & Maruping, 2021) and could include, for example, knowledge of a programming language, of project goals, and of how tasks are broken down. Common knowledge can be updated via coordination by the human agent prompting the GPT-based agentic IS artifact.

A task, for which an agent may delegate the right to another agent rights and responsibilities to execute, has three sets of attributes that are fundamental to delegation: *Action requirements, complexity, and decomposability* (Baird & Maruping, 2021). Action requirements can be either cognitive, digital, or physical. A cognitive action involves thought and abstract thinking. Such a task performed by a human agent would be associated with a cost in term of cognitive load, that is the information-processing needed to be done for the task (Fagerholm et al., 2022). The equivalent of cognitive load for a GPT-based agentic IS artifact would be something akin to Graphical Processing Unit (GPU)-cycles. A digital action could be, for example, writing code or executing a program. A physical action could be, for example, typing on a keyboard. Task complexity is associated with uncertainty in decision making, interdependence between decisions and between agents, and with the dynamics of a system (Baird & Maruping, 2021). More complex tasks can be assumed to take more resources to execute. This is true not only in the case of computing resources, such as memory and CPU- or GPU-cycles, but also when it comes to cognitive load where task complexity increases cognitive load (Fagerholm et al., 2022) on the human agent executing the task.

Task execution can result in outcomes including goal attainment, progress, or failure (Baird & Maruping, 2021).

Tasks are not executed in a vacuum, and Baird & Maruping (2021) specify situational attributes that can influence both the agentic relationship as well as outcomes. The first attribute, *Incentives (Extrinsic)* can be, for example, a monetary reward. The second attribute, *complexity*, is divided into *stability, observability and controllability (Baird & Maruping, 2021)*. Stability could refer to e.g., the tendency of requirements to change over time. Observability refers to "the transparency (or opacity) of the situation, with respect to being able to understand the states of the system, given what is measured and known" (Baird & Maruping, 2021, p. 327). An example could be working with open source versus closed source software. Controllability refers to the degree to which the agents have regulatory control over the situation in regard to manipulating inputs to achieve a certain output (Baird & Maruping, 2021).

Finally, feedback loops from observed outcomes can impact appraisals, shape future decisions on further delegation (Baird & Maruping, 2021) as well as coordination.

3. Method

For data collection we conducted semi-structured interviews, which we then transcribed and analyzed using directed content analysis (Hsieh & Shannon, 2005). In this way, we took an interpretive approach to studying agentic relationship dynamics as a sociotechnical phenomenon, which we deemed appropriate as interpretive research has been shown potential for providing deep insights into IS-related phenomena (Klein & Myers, 1999).

Data collection was done in an IS education context with second-year students learning object-oriented programming, relational databases, and systems integration. We conducted a total of 17 face-to-face interviews (see Table 1). Data collection inside of the IS education context was favorable since our status as an academic institution allowed us to become early adopters of the technology, and experiment freely with generative AI. Since the code worked on by students was not proprietary, sensitive or secret, and since the consequence of task failure is relatively low (Dwivedi et al., 2023), early adoption was possible.

3.1. Research setting

The study was undertaken in the context of a course on IT Architecture and Software systems, a part of a three-year bachelor programme in design of Information Systems, in Sweden. The interviewees were second year students with experience of programming in Java, C#, as well as programming for the web. The students also completed courses in relational databases with SQL, and systems integration using Java, C#, with SOAP and REST web services.

Students had been encouraged during the course to use both ChatGPT and GitHub Copilot to complete programming assignments. For one minor programming assignment, ChatGPT use was mandatory, and writing code or systems manually was prohibited in order to make sure that students try out, and engage with, generative AI. The assignments took the form of projects with fictional businesses with fictional requirements that the students had to design databases and author software to fulfill. Thus, this study was not undertaken in any kind of controlled environment or using any type of experimentation.

3.1. Data collection

Interview questions for the face-to-face semi-structured interviews were open-ended and centered around the elements and mechanisms in the IS Delegation Framework (Baird & Maruping, 2021). We initially send out invitations to participate by email which 17 persons replied to and were interviewed (see Table 1). All interviewees had used ChatGPT for software development, some had also used GitHub Copilot. Interview subjects 4 and 11 had minor extracurricular experience of programming from taking courses outside of the study programme. Interview subject 1 had significant programming experience of 10 years including professional experience. All interviews were conducted over a period of two weeks after, starting after the software development projects had been examined, to make sure that interviewees' experiences were fresh in their minds. The researcher conducting the interviews was also the teacher on a part of the course and was thus intimately familiar with details regarding coursework and with the software and GPTs used.

Table 1. Interview subjects

Subject	Length	AI applications
Subject 1	1h 43m	ChatGPT and Copilot
Subject 2	1h 15m	ChatGPT and Copilot
Subject 3	1h 31m	ChatGPT
Subject 4	1h 13m	ChatGPT
Subject 5	1h 20m	ChatGPT, minor use of Copilot
Subject 6	1h 52m	ChatGPT
Subject 7	1h 30m	ChatGPT
Subject 8	1h 11m	ChatGPT
Subject 9	1h 37m	ChatGPT and Copilot
Subject 10	1h 08m	ChatGPT and minor use of Copilot
Subject 11	1h 30m	ChatGPT and Copilot
Subject 12	1h 16m	ChatGPT
Subject 13	1h 36m	ChatGPT
Subject 14	1h 57m	ChatGPT and minor use of Copilot
Subject 15	1h 34m	ChatGPT
Subject 16	1h 48m	ChatGPT
Subject 17	1h 54m	ChatGPT and minor use of Copilot

3.2. Data analysis

We transcribed all 17 interviews from their audio recordings using OpenAI Whisper Large Language Model. We then went over the transcripts, with the help of the audio recordings, and corrected formatting as well as any errors made by the model. In a first step, the transcriptions were then analyzed in MAXQDA using directed content analysis (Hsieh & Shannon, 2005). Directed content analysis uses pre-defined categories for coding, and can be used to conceptually extend an existing theory or to provide insight on the relationships between its constituent concepts (Hsieh & Shannon, 2005). We coded all of the transcripts according to the pre-defined categories found the IS Delegation Framework (Baird & Maruping, 2021), such as endowments, delegation mechanisms, and task attributes. We coded on paragraph-, sentence-, and sub-sentence level. Since we were looking for relationships and interactions between pre-existing elements and mechanisms of the IS Delegation Framework, we did not code, or use codes, that were not derived from the framework. Thus, instances of data which did not concern the IS Delegation Framework were not coded. In the second step of analysis, we went over the transcripts again, and looked for patterns in the coded data where different elements and mechanisms of the IS Delegation Framework were repeatedly found to interact. These recurring patterns became the basis for what we label "agentic relationship dynamics".

3.3. Ethics

To ensure informed consent, every participant was informed, in writing and before agreeing to participate, about the study's purpose and procedures. They were informed that their identities would remain anonymous, and that no data collected would be shared with persons outside of the research project, their rights under the European Union's General Data Protection Regulation, and that their consent could be withdrawn at any time. Every participant signed a consent form to the effect that they had understood the procedures. The participants were also informed, prior in writing and verbally at the time of the interviews, that anything that they would bring up during the interviews would not affect their present or future studies in any way. We tried to make it as clear as possible that the interviews were not a form of examination or knowledge control and that we were solely interested in the participants' experiences.

4. Results

Mapping our data onto the IS Delegation Framework (Baird & Maruping, 2021), as shown in Figure 2, we found patterns of attributes and mechanisms that appeared to be particularly significant for delegation.

Human agents' knowledge (e.g., of programming), memory (e.g., of project objectives), judgement, intuition, creativity, focus, attention to detail, motivation, and confidence (e.g., in tackling coding-related problems) were perceived to be particularly important for, or were particularly affected by delegation.

As for capabilities, the developers' reasoning abilities, problem solving skills, ability to think

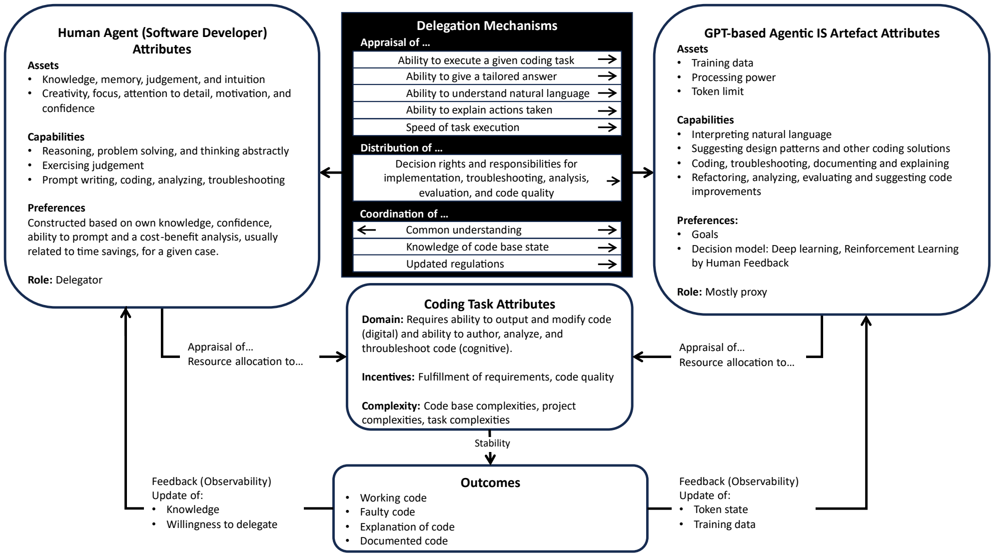

Figure 2. Applied IS Delegation Framework

abstractly, and to exercise judgement were central. Skills relevant to delegation were prompt writing, coding, analyzing (of code, mostly), and troubleshooting. These relativeness of these endowments to the endowment of a GPT-based agentic IS artifact (in this chapter referred to as a 'bot'), played an important role in appraisal and delegation. Human agent preferences consisted of their knowledge, confidence, prompting ability, and of a cost-benefit analysis, especially related to time savings.

For sake of delegation, the training data, (perceived as the agentic IS artefact's "knowledge"), processing power, (perceived as the bot's ability to think and problem solve, and its attention to detail), and the token limit proved to be significant.

For capabilities, the bots' ability to process natural language, enabling coordination and regulation, was central for enabling delegation. Furthermore, suggesting patterns and solutions, coding, troubleshooting, documenting, and explaining code and concepts were found to be important capabilities. The bots were also perceived to be good at processing code, with refactoring, analyzing, evaluating, and suggesting improvements being relevant capabilities for delegation. The bots, in contrast to the humans, have preferences built into them as a result of Reinforcement Learning by Human Feedback.

We found five key unidirectional appraisals with the human agents appraising the endowments of the bots in terms of their abilities to execute coding- or coding-related tasks. These included appraisals of bots' capabilities, but also of the bots' endowments in terms of training data and processing power from which their capabilities arise. The other recurring appraisals were of the bots' ability to give an answer tailored to the human agent's situation or case, to understand a question in natural language, to explain actions taken and thus provide transparency, and the speed at which the bot could execute tasks.

The distribution of rights and responsibilities were also unidirectional being passed through direct transfer or negotiation from the human agent to the bot. Direct transfer was the most common mode, although negotiation between the agents did take place where regulations of task execution, such as practices to follow, were set.

Coordination was done mostly by human agents apart from a few instances where the bots asked for clarifications or additional information.

Coding-related tasks require cognitive actions to solve and digital actions to execute. Tasks would be subject to situational complexities (Baird & Maruping, 2021) inherent in the software frameworks, projects, and tasks. Some complex tasks, such as authoring a Data Access Layer component could be subject to further decomposition.

Multiple feedback loops were observed in cases of authoring, evaluating, and troubleshooting of code with a human agent and a bot working iteratively together on solving a problem.

We found five salient dynamics, related to tasks being delegated and executed, that affected elements such as appraisals and endowments and thus the agentic relationship. We will now describe these agentic relationship dynamics below.

4.1. Dynamic 1 - Common understanding builds and diminishes as the agentic relationship progresses

Common understanding regarding was perceived as crucial for successful delegation. Participants reported that their productivity increased in areas where they possessed more knowledge. They also reported that productivity decreased, and that delegation was more difficult, when they perceived that they were too far outside of the bounds of their knowledge and capabilities. In addition, participants also perceived a substantial risk of not being able to exercise judgement in validating code authored by the bot: *"If you cannot validate what it outputs then it is quite likely that it has done something whack that just… It is something that I have had to learn the hard way. That you can waste a lot of time when you are trying to work on something that is not at your level of understanding. And [the bot] just produces things that you cannot validate"* (Interview subject 17).

Additionally, when the participants operated outside of the bot's knowledge cutoff, or in areas not covered in training data, productivity was perceived to drop as coordination costs of keeping common understanding synchronized were incurred:

Participants reported that as work progressed, they learned more and more from working with, and prompting the bots: *"[…] you also learn a lot from it… situations where certain things can be used that one may not have reflected on or implemented by oneself prior"* (Interview subject 1).

The participants would ask the bots to explain code that they had found online, code written by team members, and code that the bots had authored. The bots were perceived as being adept at explaining and teaching. Moreover, the bots were perceived, given adequate prompting, as being flexible in their way of tailoring explanations, using e.g., analogies and metaphors. The ability to iteratively ask follow-up questions was also perceived to be helpful for lessening the knowledge gap between the participant and the bot.

When it came to the codebase itself, especially ChatGPT was perceived as having limitations that impacted collaboration. Due to its inherent token limit, the bot can only "remember" a certain amount of content. Participants reported that they could not trust or rely on the bot to remember what they had told it previously about the state of their project and of their code: *"It can forget. It forgets things like the consequences of certain relationships between different entities and, yeah, I do not trust it as much when it comes to those kind of things"* (Interview subject 11).

While knowledge, in general, was perceived to be asymmetrically tilted towards the bot knowing more than the human due to its vast set of training data, knowledge of the project and the state of the codebase was asymmetrically tilted towards the human remembering more than the bot. This would lead to coordination costs for participants in keeping the bot up to date with the state of the project, the codebase, and regulations. Thus, common understanding required for the task at hand would diminish on part of the bot would need to be updated further down the line: *"It is also a problem stemming from a limitation on the number of tokens it can hold in memory at once. At a certain point it will forget about what it is doing"* (Interview subject 11).

4.2. Dynamic 2 – Agentic IS artifact perceived performance impacts willingness to delegate

Participants reported that they were more likely to delegate tasks to bots in areas which they expected the bots to perform well, or where they had perceived the bots to perform well in the past.

The bots' knowledge as it came to subject matter was perceived to be vast and participants reported that they would not hesitate to prompt the bots on any topic. The bots' knowledge on language- and environment-specific errors was perceived to be especially helpful by participants.

Participants reported that the speed at which the bots could process information, and thus quickly detect errors that were not picked up by integrated development environments made an impression on participants, and future willingness to delegate. They perceived that the bots had superior attention to detail: *"If I misspell in a method, I will notice it immediately. However, if I misspell in a query [inside of a string] then I may not notice it. That kind of thing has really been eliminated […]. [the bot] sees it immediately."* (Interview subject 16).

Bots' abilities to solve, or help solve, difficult errors or bugs was reported to be a major motivator for delegation. However, errors that may have been discovered after, or would only appear in versions of software released after, the bots' knowledge cutoffs were perceived as more difficult to solve: *"If it is new errors, and if the organization, for example Oracle, does not even know about the error themselves then [the bot] will have a very difficult time"* (Interview subject 17).

The bots were also perceived to struggle, due to their token limitations, when troubleshooting involved multiple software components and in some cases even server components. This increased coordination costs of having to provide the bots with code from different system components during troubleshooting: This led to participants deciding partially or fully avoid delegation of such complex tasks, as the success rate was perceived to be low, and the coordination costs were perceived to be high.

4.3. Dynamic 3 – Delegation reduces cognitive load on human agents

Participants reported that delegation led to reduced cognitive load in several ways. Analyzing code authored by a bot was perceived to be less demanding than authoring manually: *"I think that it makes light-years of difference. I think that it is much easier to look at a relatively complex method and say what everything does than sitting and writing a basic method." (*Interview subject*, 17).*

Delegating authoring to the bots meant that participants avoided spending cognitive effort on the mechanical work of typing, of spelling correctly, of thinking of how to structure the code, and of keeping those structures in mind while working.

Participants also reported reductions in cognitive load due to delegating troubleshooting. Participants perceived the bots to be protecting them from the information overload inherent in search engine results. They would not have to view, and sort through links to websites resulting from a search, and, they did not have to navigate pages to look for a solution or adapt it to fit their specific case. Instead, the bots were able to provide them with information and code tailored to their specific scenario: *"[…] but ChatGPT gives a specific answer to my question and if I would google that question I would get a greater span of answers or proposed solutions".* (Interview subject 13).

Prompt writing was often perceived by the participants to cause less cognitive load than performing the delegated task themselves. Participants also reported less cognitive load from creative work, delegating to bots to come up with believable test data. Several participants perceived that they felt that they had become lazy by delegating coding-related tasks to the bots: *"I am afraid that you become a bit too lazy by using [the bot]. It is a bit too easy to find things, solve certain parts, that you do not even bother to… It is that easy to have ChatGPT do it, and then you do not have to think about it anymore"* (Interview subject 1).

The reduction in cognitive load due to delegation enabled participants to work for longer bouts. Some participants reported that when they did encounter fatigue, their use of bots increased, as well as their reliance on the bots in terms of, for example, the time that they would spend trying to solve an issue with a bot before switching over to manual troubleshooting: *"The mental load of making the same amount of progress would probably have been a lot greater [without using bots]. Then it would not have been 8 hours, then it would have been like 30 hours, and you cannot work for 30 hours straight. So in that sense I think that it saves a lot of mental energy".* (Interview subject 17)

4.4. Dynamic 4 – Successful delegation increases self-reported confidence

The use of bots increased participants' reported confidence in terms of what tasks they believed that they could take on and. This was perceived to be especially true for troubleshooting, where several participants reported that not only did they manage to solve problems and get "un-stuck" faster than they could without the use of bots, but they were also not afraid of getting stuck anymore.

"If I get stuck now my first thought is not that 'Oh my god… now we will be stuck on StackOverflow for three hours', instead it is that 'Okay, I will look up what the error is and I will be out of there in 10 minutes maximum'. And then I can keep doing what is fun" (Interview subject 15).

This reported increase in confidence allowed participants to tackle problems or attempt to implement solutions or design patterns that they previously would have thought to be too difficult.

"It gives you a lot of confidence as to what you can take on […]. There is really nothing now that I feel like "I cannot take this on". It is whatever. ChatGPT will always have an answer as long as it is not something astronomically difficult". (Interview subject 17).

4.5. Dynamic 5 – Human agents breaking GPT-based agentic IS artifact "thought loops"

Several participants reported encountering situations where the bots would appear to get stuck in what they described as thought loops, cycling through the same answers over and over. This was reported to happen in, for example, troubleshooting scenarios where the participant and the bot are having a dialogue trying to solve a technical issue.

"[…] we tried every solution under the sun that it suggested, and then it kind of always goes back to something that we tried already. You get stuck in a cycle. […] And then I say 'Okay, this does not work, I think it has to do with this instead, can we try that?'. And it agrees to do it. Because then, even if my initial idea should prove to be wrong, you can get onto another track and it might be that something in relation to that idea was the cause of the error. But then ChatGPT […]

has broken its loop and is now thinking about other things" (Interview subject 17).

The bot would have to be explicitly prompted by the human to break its loop. Introducing contextual information and regulations was also reported to prevent bots from getting stuck in loops.

Thus, instead of moving on, the participants actively prompted the bot to try to get it to "think" in new and different ways. The narrow perspective brought about by its token limitation could then be complemented by the wider perspective of the participant, allowing them to let the bot use different parts of its wider array of knowledge to help the participant solve the issue at hand.

5. Discussion

Here follows a discussion of the five agentic relationship dynamics found followed by a discussion of the limitation of the study.

5.1. Dynamic 1 - Common understanding builds and diminishes as the agentic relationship progresses

Our findings highlight the importance of overlap in common understanding (Baird & Maruping, 2021) between the human agent and the GPT-based agentic IS artifact. Overlap in regard to the subject matter of the task, in this case programming, was perceived to be especially important for successful outcomes of delegations. This is likely due to the nature of the prompt-based interactions with the GPT-based agentic IS artifacts. The content of the generated response is highly dependent on the prompt. We found that in areas where the GPT-based agentic IS artifact possesses large amounts of training data, the more overlap in common knowledge on the part of the human agent, the better the preconditions for successful delegation. In addition to this we found that prompting, viewed apart from common knowledge, is a skill in itself, and that the usefulness of a generated response would vary depending on the way in which the corresponding prompt was written. In other words, common knowledge for authoring and evaluating, as well as prompt writing skills are preconditions for successful delegation.

Our findings show increases in common understanding, on the part of the human agent, as the agentic relationship progressed. Learnings were perceived to stem from both prompts explicitly asking for explanations, but also from follow-up prompts. Thus, an iterative feedback loop of follow-up prompts expanded the overlap of common knowledge with the agentic IS artefact. As proposed in (Slaughter & Chen, 2021), the GPT-based agentic IS artifact, taught the human agent as the agentic relationship progressed, affecting their endowments and thus preconditions for future appraisals and delegations.

Human agents were likely to know more about project goals, boundaries, and requirements than the agentic IS artefacts, as such project-specific information does not exist in training data. In the case of ChatGPT, any such information vital to task execution would incur a coordination cost on the human agent in terms of maintenance of common knowledge. The retention of this knowledge in the agentic IS artefact was also subject to the limitation in how many tokens GPT-based IS agentic artifacts can hold in memory at a given time, incurring further coordination cost that human agents, as delegators, would always be willing to pay, in which cases they would abstain from delegating.

This adds nuance to the proposition of Baird & Maruping (2021) relating to asymmetries between agents. While our results confirm this asymmetry in terms of capabilities, as pointed out by the authors, we can also point to an asymmetry in knowledge favoring the GPT-based agentic IS artefact in the case of general knowledge, and the human agent in the case of situation- or project-specific knowledge. Our results indicate that these asymmetries matter for coordination, coordination costs, and for willingness to delegate.

5.2. Dynamic 2 – Agentic IS artifact perceived performance impacts willingness to delegate

Our findings confirm the proposition by (Baird & Maruping, 2021) that successful delegation outcomes may increase future willingness to delegate.

Appraisals by human agents (Baird & Maruping, 2021) of the endowments and capabilities of GPT-based agentic IS artifacts played a key role in delegation. Appraisals could be based on pre-conceived notions, but also on outcomes from execution of tasks previously delegated. We found that perceived vastness of a GPT-based agentic IS artifact's training data (often perceived and described as its "knowledge") on a given subject, would increase human agents' willingness to delegate tasks related to that subject.

A precondition, however, was that the agentic IS artefact would also have to be perceived as capable. Our result show that in areas such as Graphical User Interface design, an agentic IS artefact could be perceived as "knowledgeable", while at the same time being perceived as lacking capability. This perception was often based on outcomes of past delegations and resulted in a lower willingness to delegate tasks relying on such capabilities.

Apart from capability, speed of task execution on part of the GPT-based agentic IS artefact was also appraised as important for willingness to delegate.

We found that factors not directly related to agentic IS artefact capabilities could also impact performance. Task complexity (Baird & Maruping, 2021) in combination with token limitations in GPT-based agentic IS artefacts could impact delegation outcomes, and thus future willingness to delegate on part of the human agent as coordination and imposing regulations became more difficult. Prompting skill on part of the Human agent was also found to impact outcomes, and thus potentially willingness to delegate.

5.3. Dynamic 3 – Delegation reduces cognitive load on human agents

Our results indicate a reduction in cognitive load (Fagerholm et al., 2022) on human agents as a result of delegation. Writing a prompt and evaluating the result, e.g., code, was perceived to have less of an impact on cognitive load in human agents compared to authoring the code manually. Authoring, for example code, would require human agents to consider structure and spelling as well as performing the mechanical work associated with the physical action (Baird & Maruping, 2021) of typing. Delegation lessened the perceived cognitive load associated with tasks involving authoring.

Complex tasks, such as troubleshooting, were also perceived to increase cognitive load when done manually, and especially if the task required close attention to detail. Delegation of such tasks was also reported to reduce perceived cognitive load.

Lastly, the reduction in cognitive load, stemming from human agents' ability to delegate (Baird & Maruping, 2021) as described, was reported to enable human agents to work for longer periods of time on cognitively demanding work in a more focused manner.

5.4. Dynamic 4 – Successful delegation increases self-reported confidence

Our results indicate that successful delegation to GPT-based agentic IS artifacts could impact the decision model (Baird & Maruping, 2021) of human agents in terms of confidence. The gain in confidence, in turn, positively affected their perception of their own ability to take on difficult tasks. The reported confidence increases also led to a perceived sense of self-reliance in human agents, even in scenarios where they did not have access to a GPT-based agentic IS artifact. This was coupled with a reported sense of momentum and increased ability to stay focused.

5.5. Dynamic 5 – Human agents breaking GPT-based agentic IS artifact "thought loops"

The complementary nature of human agents and agentic IS artifacts has been discussed at some length (see e.g., Baird & Maruping, 2021; Fügener et al., 2022). Our results show that the "thought loops", that GPT-based agentic IS artifacts were reported to get stuck in, can be broken through skillful coordination on part of the human agent. The human agent could, using prompting, help and steer the GPT-based agentic IS artifacts towards more productive lines of reasoning. This would be an example of a capability asymmetry (Baird & Maruping, 2021) the human agent complement the GPT-based agentic IS artifact in a way that supports the functioning of the agentic relationship in the dyad.

5.6. Limitations and future research

The study was conducted with students with mostly limited experience of software development. Since more extensive knowledge within a given subject area appears to lead to greater utility of e.g., ChatGPT and Copilot within that area it is possible that the results would be different if carried out with experienced software developers. However, while the outcomes observed by the participants may have been different had they had more experience, it is not obvious to us that they agentic relationship dynamics at play would have been different in their nature.

Although the study is limited to 17 interviews, we deem that we reached a saturation in the data in relation to themes brought up by interview subjects.

The study was not done in an experimental setting. The course setting, with its' project assignments, requirements, tools, and frameworks, was purposely set up to mirror IT industry work practices. Agentic relationship dynamics discovered in this setting are, we argue, more likely to mirror those present in a corresponding industry setting.

Future studies on agentic relationship dynamics could be conducted in an industry setting to perhaps uncover dynamics, or ways in which dynamics manifest, that is specific to that setting.

6. Conclusions

In this paper we explored agentic relationship dynamics in a setting involving human agents and GPT-based agentic IS artifacts which, to our knowledge, has not been done previously. By drawing upon the IS Delegation Framework by (Baird & Maruping, 2021) for explaining delegation we can point to five salient dynamics, involving foundational delegation mechanisms of the framework, that have significant effects on agentic relationships: Common understanding building through an iterative feedback loop and diminishing due to the GPT token limitation as the agentic relationship progresses, GPT-based agentic IS artifact perceived performance impacting willingness to delegate, delegation reducing cognitive load on human agents, successful delegation increasing self-reported confidence and willingness to take on difficult tasks in human agents, and human agents breaking GPT-based agentic IS artifact "thought loops" by skillful prompting. Through these agentic relationship dynamics, the human agent and the agentic IS artifact complement each other's capabilities and limitations in a symbiotic agentic relationship dyad. By shedding light on these dynamics, we can provide insight into agentic relationship dynamics for practitioners that use GPT-based agentic IS artifacts for cognitive tasks.

7. References

Alter, S. (2022). Agent Responsibility Framework for Digital Agents: Roles and Responsibilities Related to Facets of Work. *Enterprise, Business-Process and Information Systems Modeling*, 237–252.

Baird, A., & Maruping, L. M. (2021). The Next Generation of Research on IS Use: A Theoretical Framework of Delegation to and from Agentic IS Artifacts. *MIS Quarterly*, *45*(1), 315–341.

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D., Wu, J., Winter, C., … Amodei, D. (2020). Language Models are Few-Shot Learners. *Advances in Neural Information Processing Systems*, *33*, 1877–1901.

Christiano, P. F., Leike, J., Brown, T., Martic, M., Legg, S., & Amodei, D. (2017). Deep Reinforcement Learning from Human Preferences. *Advances in Neural Information Processing Systems*, *30*.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). "So what if ChatGPT wrote it?" *International Journal of Information Management*, *71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Ellinger, E., Mini, T., Gregory, R., & Widjaja, T. (2021). *Facilitating Collective Action in Agentic IS Platforms: The Case of Decentralized Autonomous Organizations* (SSRN Scholarly Paper 3938489). https://doi.org/10.2139/.3938489

Else, H. (2023). Abstracts written by ChatGPT fool scientists. *Nature*, *613*(7944), 423–423.

Fagerholm, F., Felderer, M., Fucci, D., Unterkalmsteiner, M., Marculescu, B., Martini, M., Tengberg, L. G. W., Feldt, R., Lehtelä, B., Nagyváradi, B., & Khattak, J. (2022). Cognition in Software Engineering: A Taxonomy and Survey of a Half-Century of Research. *ACM Computing Surveys*, *54*(11s), 1–36.

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2022). Cognitive Challenges in Human–Artificial Intelligence Collaboration: Investigating the Path Toward Productive Delegation. *Information Systems Research*, *33*(2), 678–696.

Hsieh, H.-F., & Shannon, S. E. (2005). Three Approaches to Qualitative Content Analysis. *Qualitative Health Research*, *15*(9), 1277–1288.

Kalliamvakou, E. (2022, September 7). Research: Quantifying GitHub Copilot's impact on developer productivity and happiness. *The GitHub Blog*. https://github.blog/2022-09-07-research-quantifying-github-copilots-impact-on-developer-productivity-and-happiness/

Klein, H. K., & Myers, M. D. (1999). A Set of Principles for Conducting and Evaluating Interpretive Field Studies in Information Systems. *MIS Quarterly*, *23*(1), 67. https://doi.org/10.2307/249410

Liu, J., Yue, W. T., Leung, A., & Zhang, X. (2022). *Find the Good. Seek the Unity: A Hidden Markov Model of Human-AI Delegation Dynamics* (SSRN Scholarly Paper 4150772). https://doi.org/10.2139/ssrn.4150772

Lorenz, J., & Recker, J. (2023). *Where Digital Innovation Meets the Human Body: Somatic IS Artifacts and Entanglements*.

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). *Improving Language Understanding by Generative Pre-Training*.

Slaughter, K. T., & Chen, D. (2021). Is Knowledge Power or Ignorance Bliss? Delegate and Educate in Robo-advising: A Proposed Study of the Human-Agentic IS Artifacts Dyad's Shared Domain Knowledge. *AMCIS 2021 Proceedings*, *3*.

Thorp, H. H. (2023). ChatGPT is fun, but not an author. *Science*, *379*(6630), 313–313. https://doi.org/10.1126/science.adg7879

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is All you Need. *Advances in Neural Information Processing Systems*, *30*. https://doi.org/10.5555/3295222.3295349

Zou, Y., & Lei, Z. (2021). Promoting Gains vs. Preventing Losses: Augmenting Investment Decisions through Regulatory Foci in Robo-Advisors. *ICIS 2021 TREOs*, *45*.