Task Delegability to AI: Evaluation of a Framework in a Knowledge Work Context

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Abstract

With the increased research focus on ways to use AI for augmentation rather than automation of knowledge-intensive work, a myriad of questions on how this should be accomplished arises. To break down the complexity of Human-AI collaboration, this paper pursues the identification of factors that contribute to the delegation of tasks to AI in such a setting, and consequently gain insights into requirements for meaningful task allocation. To address this research gap, we carried out an empirical study on an existing task delegability framework in a knowledge work context. We employed several statistical approaches such as confirmatory factor analysis, linear regression, and analysis of covariance. Results show that an adapted framework with fewer factors fits the data better. As for the framework factors, we show that the factor trust predicts delegability best. Furthermore, we find a significant impact of task on delegability decision. Finally, we derive theoretical and design implications.

1. Introduction

Artificial intelligence (AI) is the science and engineering behind creating intelligent machines, particularly computer programs, which try to grasp and, to some extent, imitate human intelligence [1]. With the rise of AI, concerns about automation and consequent job loss have increased [2]. Galore research still focuses on finding ways to automate work with AI, without considering these consequences. However, in the last decade, researchers started giving rise to the importance of keeping the human-in-the-loop [3]. Furthermore, growing evidence of the advantages of Human-AI collaboration started appearing in the literature. This marks a shift to a collaborative rather than automation perspective of AI [4]. For example, Dellermann et al. [5], and Bittner et al. [6] argue that combining complementary strengths of human intelligence and AI leads to a better performance than each could achieve separately. Not only does this improve the outcome and group performance, but such a constellation also significantly contributes to mutual learning [7]. However, there is a long way to achieve the optimal collaboration for such socio-technical ensembles [8], and various research gaps to address in the first place. First of all, a realignment of the task allocation is necessary because the challenges of the modern world of work exceed the abilities of individuals [6]. In addition, the interplay between humans and tasks while collaborating with AI (assistants) as well as the outcomes of this collaboration necessitate further investigation. An AI assistant helps users achieve their tasks by interacting with them while using machine intelligence in form of, e.g., natural language processing, speech recognition, or machine learning [9].

AI capabilities are opening up new pathways for collaboration between knowledge workers and machines. Knowledge workers' main attribute is knowledge. They apply this knowledge to develop products and services [10]. As knowledge work gains in complexity, it is becoming more and more challenging for individuals [11, 12]. Technological advances in the field of AI offer new design opportunities for the reorganization of knowledge work at the interface of humans and AI [13]. Many knowledge-based tasks can now be solved more effectively with AI technologies than with earlier technologies. For example, AI can be used to automate Q&A, enabling humans to focus on high-level interactions. But to take full advantage of the prospects of Human-AI collaboration in knowledge work, companies will have to redesign knowledge-work processes and jobs [14]. The existing potential for automation of tasks in knowledge work does not directly correspond to increased performance [15]. In contrast, AI assistants should be designed with the intention to augment, not replace human contributions [16]. Oeste-Reiss et al. [13] introduce Hybrid Knowledge Work Systems that continuously enable knowledge workers to acquire and transfer knowledge for the performance of their work tasks by means of hybrid intelligence [5]. Such systems

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help knowledge workers by relieving their cognitive load and supporting the work process. This causes a shift in the division of labour between knowledge workers and AI assistants and increases the proportion of tasks that can be completed by humans and AI assistant(s) as a team [13]. For a meaningful task allocation in such a constellation, it is first necessary to identify the factors that influence this allocation in either a positive or negative way. This area of Human-AI collaboration is underexplored, especially from a point of task delegation. To the best of our knowledge, there is only one developed framework of task delegability [17]. The relatively novel framework was developed for (potentially AI-supported-)work in general and is now to be examined whether it also provides explanatory contributions for knowledge work. It is hard to make inferences about the applicability of the framework to more specific contexts, such as knowledge work in postgraduate research, an exemplary class of knowledge work fulfilling necessary criteria for our study scope (see section 3.2). To address this research gap, this study aims at answering the following research questions:

- **RQ 1:** How does the existing framework of task delegability apply to a specific context of knowledge work in postgraduate research?

The existing framework indicates different correlations of components to the delegation decision [17]. The question arises whether and to what extent are these present in the current context as well. Thus, we are also interested in answering:

- **RQ 2:** Which components of the framework contribute most to the delegation decision?

Finally, the framework authors found that some tasks are rather delegated than other [17]. This motivates the following question, specifically relating to knowledge-intensive tasks:

- **RQ 3:** Does the delegation decision depend on the task?

The goal of the study is to validate and further develop the framework in a new application context and better understand the delegation decisions of knowledge workers, especially researchers, and their influencing factors, in order to derive design knowledge for Human-AI collaboration.

2. Theoretical Background

2.1. Human-AI Collaboration

To overcome limitations of humans and AI alone, Dellermann et al. [5] propose a construct of Hybrid Intelligence, which they define as:

> ”The ability to achieve complex goals by combining human and artificial intelligence, thereby reaching superior results to those each of them could have accomplished separately, and continuously improve by learning from each other.”

Achieving this predisposes collaboration between humans and AI. Hybrid collaboration involves at least two actors (at least one being human and one AI) having the same understanding of a shared goal and working together toward this mutual goal [18, 19, 6]. Examples of Human-AI collaboration can be seen in clinical decision support systems and customer service chatbots [19, 20]. There are many advantages to Human-AI collaboration, e.g., it improves group performance [21, 22], inter alia. Still, there are also many unresolved questions about human-AI teams dynamics and characteristics as well as about the transferability of concepts from solely human teams [23]. Human-AI collaboration, where both actors collaborate in an equal partnership is yet at an early stage of development, but it is becoming an increasingly important research area in the fields of Human-Computer Interaction and Information Systems [18]. Previous research emphasizes the importance of considering design issues for Human-AI collaboration. Among those are the design of explainable and transparent AI agents, and the design of a common workplace with consideration of tasks and roles [24].

2.2. Task allocation in Human-AI Collaboration

There is a myriad of challenges to consider when designing human-AI systems for collaboration purposes. One of the fundamental issues hereby is the task allocation between humans and AI [25]. The labour division aims to strengthen the human-centered design of the human-AI interaction and to sustainably relieve and support employees in their work [26]. To address this issue, several authors argue for the allocation of tasks according to corresponding strengths. In this regard, it would make sense to allocate routine tasks to AI, while humans focus on creative non-routine tasks requiring out-of-the-box thinking [5, 27, 12]. However, this would only be one dimension of the solution, as other influencing factors need further consideration, such as human preferences for certain tasks and readiness to delegate tasks to AI. The task allocation should furthermore be tailored to the qualifications and skills of the users - both in terms of the content and the form of interaction (e.g., reaction times or workload). Moreover, [26] points out that a high degree of agency and situation control can prevent dissatisfaction among employees. When it comes to the allocation content, an empirical study about the use of virtual collaborators [28] shows concrete examples of tasks that, according to study participants, should and can be done by a virtual AI assistant. Those are, for example, conducting systematic literature reviews, organizing appointments, and assisting in writing a mid-term paper.

2.3. Task Delegability

Delegation implies entrusting authority to another person or, since last century [29], to computers. The goal of it is to lay off a part of the workload and distribute labour in efficient ways [30]. According to Milewski [30], several factors affect delegation, namely: Perceived delegate performance, trustworthiness, similarity to the delegator, confidence and experience of the delegator, task type and load, and rewards and incentives.

Delegation to computer agents necessitates a rational allocation of tasks, as well as a rational decision to delegate a task to a given agent. The latter is affected by several factors, such as the ability of the agent to perform the task, the cost-benefit ratio of delegating, and trust in the agent's capability [31]. Additionally, the multitasking capabilities of the delegator directly affect the delegating decision [32]. In knowledge work professions, such as the one of a manager, delegation decision is furthermore highly impacted by the level of the importance of the task. In the case of delegating strategic decisions, it has been shown that humans are less likely to delegate to AI compared to other humans [33]. The authors explain this reluctance to delegate to AI by emphasizing peoples' need for proximity to individuals they see as supportive, hence the lack of such perception in the context of AI complicates the delegability. Milewski and Lewis [34] argue that delegation decision also pertains to the design of intelligent agent user interfaces. Hereby, they mention several design issues that need to be addressed to increase the likeliness of delegating to intelligent assistants. In addition to previously mentioned factors, delegation also requires sophisticated, interactive communication and performance controls.

It is noteworthy that human interaction with AI comes in different types and levels, ranging from giving AI full autonomy over making decisions to not involving AI at all. In between the two extremes, there are several levels with different engagement from both sides, e.g., AI gives suggestions, or asks for feedback from humans [35].

The task delegability framework

Lubars and Tan [17] developed a framework of task delegability (see Figure 1) consisting of four high-level factors, namely: motivation, difficulty, risk, and trust. The first three factors were chosen because they affect the decision to perform a task, and trust is chosen as the most representative factor that captures the interaction between humans and AI. The framework was built on prior literature on function allocation, mixed-initiative systems, and trust and reliance on machines [36, 37, 35]. Function allocation investigates the appropriate ways to allocate tasks based on the respective strengths of human and machine [38, 35, 39]. The mixed-initiative systems are based on human-in-the-loop and computer-in-the-loop designs. The human-in-the-loop approach is based upon the interaction of humans and machines, wherein humans supervise the algorithms, leading to the improvement of the algorithmic learning as well as to more efficient performance [40, 3]. In contrast, in computer-in-the-loop approaches, humans benefit from AI support through, e.g., interpretation of large amounts of data. Furthermore, this approach improves system transparency by, e.g., reporting the uncertainty of predictions [41]. With respect to trust and reliance on machines, it is argued that trust is what drives the acceptance of AI assistance, acting as a substitute for rational decisions when there is a lack of understandability of AI output [37].

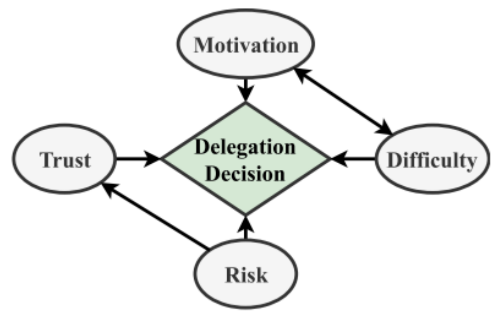

Figure 1. Framework of task delegability by Lubars and Tan [17]

Each of the framework factors consists of several components. According to the framework authors [17], they are explained as follows: Motivation is comprised of intrinsic motivation, goals, and utility, last referring to the value of the task from a cost-benefit perspective. Difficulty is framed "as the interplay between task requirements and the ability of a person to meet those requirements." Five components reflect difficulty: social skills, creativity, effort required, expertise required, and perceived human ability. Real-world tasks involve uncertainty and risk in accomplishing the task, thus they hypothetically drive delegation decision. Risk is defined through accountability for the task outcome, uncertainty, i.e., probability of errors, and impact or cost of those errors. Finally, trust comprises three components related to AI: perceived machine ability, its interpretability, and perceived value alignment.

Table 1. Overview of the framework components

Factors	Components
Motivation	Intrinsic motivation, goals, utility
Difficulty	Social skills, creativity, effort required, expertise required, human ability
Risk	Accountability, uncertainty, impact
Trust	Machine ability, interpretability, value alignment

3. Method

To address the research questions stated in the Introduction, an empirical study employing an online questionnaire was performed. 93 participants took part in the study. The data was analyzed with statistical methods appropriate for each research question, explained in detail below.

3.1. Questionnaire

The questionnaire employed by Lubars and Tan [17] was adapted to examine the preferences of task delegability to AI in a knowledge work context. Independent variables (motivation, difficulty, risk, and trust), as well as the dependent variable (delegability), were measured with the same items as in [17]. However, the questionnaire differed a lot in the tasks examined. While Lubars and Tao used 100 tasks from different areas, each answered by 4-5 respondents, we developed a list of 14 tasks, specifically tailored to our respondent group of postgraduate researchers, which are considered exemplary knowledge workers [42].

In search for relevant tasks, we used International Standard Classification of Occupations [43], from which we abstracted the tasks from various research fields to suit all respondents. Furthermore, we extracted typical research associate tasks from the German Federal Employment Agency database [44]. The tasks are diverse in terms of the four framework factors, i.e., they differ in difficulty, impact, and attractiveness for the task performer. Table 2 shows the items used to examine the four framework factors. Items in the survey were answered on a 5-point Likert scale, ranging from strongly disagree (1) to strongly agree (5). There were 14 items per task.

Finally, after answering these 14 items, participants had to decide the level of AI support they would prefer for the respective task. Four levels were offered as a possibility:

- Full AI automation: decisions and actions are made automatically by the AI once the task is assigned; you do nothing.
- The AI leads and the human assists: the AI performs the task, but asks you for suggestions / confirmation when appropriate.
- The human leads and the AI assists: you do the task mostly on your own, but the AI offers recommendations or help when appropriate (e.g., you get stuck or AI sees possible mistakes).
- No AI assistance: you do the task completely on your own.

The second and third level represent previously introduced computer-in-the-loop and human-in-the-loop approaches, respectively.

Completing the questionnaire took between 5-15 minutes, depending on the experience with the tasks and individual speed of respondents. The survey allowed a pre-selection of tasks that participants had performed during their postgraduate studies, resulting in an uneven number of answers for different tasks.

3.2. Subjects

101 subjects took part in the study on a voluntary basis. 7 subjects were removed from the dataset due to missing data (answering ”No” for every task) and one was removed after analyzing the data for outliers. The removal of the outlier did not affect the analysis results. In total, data from 93 subjects was analyzed (female = 56, male = 36, other = 1). Participants are aged 18-65, 91 % being 18-35 years old. 49 % are PhD students, 38 % master students, and the rest 13 % chose ”Other” as their occupation. Participants are employed in diverse fields of research, most commonly psychology, information systems, and computer science. The target group was students with postgraduate educational level, recruited through social media and online survey-taking platforms. Postgraduate students and research associates were chosen as a target group due to their experience with various knowledge-intensive tasks [42] as well as due to the personal involvement and different levels of responsibility they might feel for certain tasks. They are a particularly well-suited group of knowledge workers for our study goals due to the breadth of tasks they perform in their daily work-life ranging from routine to complex tasks. Moreover, IT systems where AI could be integrated are often already in use in their work processes. In addition, they could particularly benefit from AI augmentation due to the high workload and work processes profused with repetitive tasks.

Table 2. Questionnaire items

Difficulty	This task requires social skills to complete. This task requires creativity to complete. This task requires a great deal of time or effort to complete. It takes significant training or expertise to be qualified for this task. I am confident in my own abilities to complete this task.
Risk	In the case of mistakes or failure on this task, someone needs to be held accountable. A complex or unpredictable environment/situation is likely to cause this task to fail. Failure would result in a substantial negative impact on my life or the lives of others.
Motivation	I would feel motivated to perform this task, even without needing to; for example, it is fun, interesting, or meaningful to me. I am interested in learning how to master this task, not just in the completion of the task. I consider this task especially valuable or important; I would feel committed to completing this task because of the value it adds to my life or the lives of others.
Trust	I trust the AI agent's ability to reliably complete the task. Understanding the reasons behind the AI agent's actions is important for me to trust the AI agent on this task (e.g., explanations are necessary). I trust the AI agent's actions to protect my interests and align with my values for this task.

3.3. Data analysis

To investigate whether the given framework of task delegability fits the data collected in this study, we performed a confirmatory factor analysis (CFA). CFA model was fit in R programming language [45], using the laavan library [46]. The second research question concerning the impact of individual factors and components on the delegation decision was checked through linear regression. Assumptions of independence and normality of residuals as well as of homoscedasticity were analyzed via the residuals statistics and visual exploration of the residuals histogram as well as a scatter plot of observed versus predicted residual values. All assumptions were met. Analysis of covariance (ANCOVA) was employed to check whether the type of task affects delegability. To confirm that the assumptions for ANCOVA have been met, Levene's test for equality of variances was performed ($p = 0.130$), in addition to a visual check of a Q-Q plot of standardized residuals versus theoretical quantiles.

4. Results

This study investigates the fitness of the framework proposed by [17] to the data collected on a sample of postgraduate students and research associates, representative of knowledge workers. Furthermore, we analyze the impact of the framework factors on the delegibility decision, as well as whether this decision depends on the task. In further text, we present our findings corresponding to the three research questions introduced earlier.

4.1. Confirmatory Factor Analysis

The fitness of the model to the sample data was analyzed with confirmatory factor analysis. To examine whether the factor structure can be replicated, several model fit indices and their criteria were used with the given dataset: Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), Standardised Root Mean square Residual (SRMR) and Modification Indices (MI). The data included 14 items to test delegability, split into four latent factors. All 14 items are scored on a scale from 1 to 5 and treated as continuous variables in the analysis. Exploratory data analysis revealed minor deviations from normality in the distributions of few components. The model was fit using lavaan version 0.6.8 [46] in R version 4.1.0 [45]. We used maximum likelihood estimation and standardized the latent factors, allowing free estimation of all factor loadings. After analyzing the full model fit (all 4 factors, not taking into regard the covariance between variables), we decided to account for covariances between accountability and uncertainty, (MI = 6.99), social skills and creativity (MI = 8.49), and intrinsic motivation and learning motivation (MI = 11.2), since these displayed largest modification indices in the residual covariance matrix. The model fit was acceptable but not excellent, with a CFI of .95, TLI of .94, RMSEA of .06, 90% CI (.017, .090), and SRMR of .075. Further models were fit and analyzed, to investigate whether a model with a different number of factors and different variable constellation fits the data better. Led by the modification indices in the cross-loadings matrix, we decided to exclude the risk factor, exclude social skills and creativity from the difficulty factor, and include intrinsic motivation in the trust factor. This led to a model with significantly better fit than the previous model. The model fit was good with a CFI of 1.00, TLI of 1.01, RMSEA of .00, 90% CI (.00, .07), and SRMR of .055.

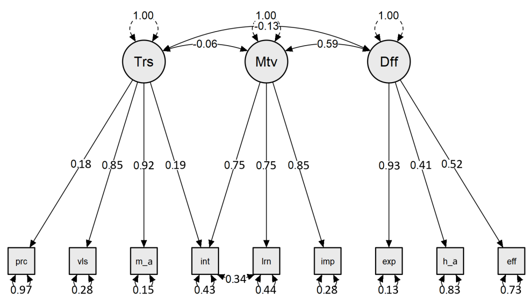

Figure 2. CFA model

Standardized parameter estimates show that machine ability and values have the highest loadings on the trust factor ($\lambda > .85$). All components of motivation have high loadings ($\lambda > .73$) on this factor. Expertise has the highest loading on difficulty ($\lambda = .94$), while effort and human ability have moderate loadings on this factor. All loadings are statistically significant ($p < 0.05$), except for the loading of the process (interpretability) on trust.

4.2. Linear Regression

Regarding the impact of individual factors and components on the delegation decision, the results of linear regression show statistically significant model fit ($R^2 = 0.460$, $p < 0.001$). The model thus explains 46 % of variance. Subsequent analysis of variance (ANOVA) shows furthermore that the model differs from null model (F = 18.491, $p < 0.001$). Trust is the factor that best predicts the delegability decision ($\beta = 0.652$, $t = 8.137$, $p < 0.001$). The regression line (Fig. 3) depicts a positive relationship between trust and delegability, i.e., the higher the trust in AI, the higher the probability to delegate a task to AI.

Motivation, difficulty, and risk have a much smaller effect on delegability compared to trust (see Table 3). Furthermore, it appears that the correlation between the 3 factors and delegability is negative, i.e. the less motivation, risk, or difficulty, the higher delegability. However, these relationships did not appear statistically significant ($p > 0.05$), meaning that there might be a trend in this particular data, but this could be due to the chance and not a reflection of the real state in population. With regard to the individual components of the factors, a component of trust, machine ability, is the best predictor of delegability decision ($\beta = 0.654$, $t = 5.406$, $p < 0.001$).

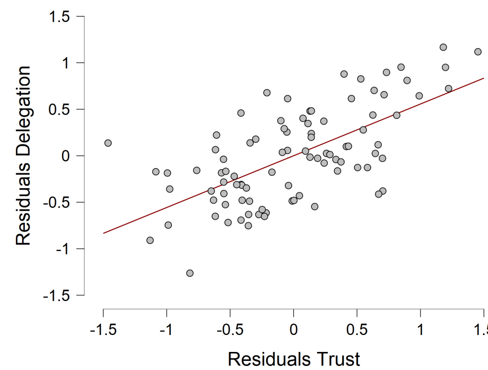

Figure 3. Relationship between trust and delegability

4.3. Analysis of covariance

A one-way ANCOVA was conducted to determine a statistically significant difference between the tasks on delegability decision, controlling for trust, motivation, risk, and difficulty. The model was estimated using the Type III sum of squares approach [47], due to uneven sample sizes. Based on the results, there is a significant effect of task on delegability after controlling for the framework factors (F = 1.860, $p < 0.05$). Task covaries with trust and motivation ($p < 0.001$). The effect size estimate ($\eta^2 = 0.031$) depicts a small effect of task on delegability. The effect of the covariance with trust appears higher ($\eta^2 = 0.244$). Without controlling for the framework factors, the effect size of task on delegability is high ($\eta^2 = 0.203$, F = 11.969, $p < 0.001$).

5. Discussion

In this study, a quantitative analysis was used to examine a framework of task delegability to AI in a knowledge work context, i.e., to examine human preferences to involve AI into their work either to a certain level or by delegating the complete task.

5.1. Theoretical implications

Our findings contribute to the literature on task allocation and delegability to AI, especially in the context of Human-AI collaboration in knowledge work. We found that the framework with four factors does not provide the best fit in this specific knowledge work context and that the model with a reduced number of factors best represents the answers of the study participants. Thus, a framework of task delegability can

Table 3. Regression Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	2.441	0.055		44.620	$< .001$
H_1	(Intercept)	1.234	0.448		2.753	0.007
	Difficulty	-0.094	0.106	-0.081	-0.891	0.375
	Motivation	-0.075	0.064	-0.113	-1.158	0.250
	Risk	-0.049	0.060	-0.071	-0.809	0.421
	Trust	0.568	0.070	0.652	8.137	$< .001$

Table 4. Effect of task on delegability

Task	Mean	SD	N
Code and verify data in accordance with specified research protocol	3.150	0.662	40
Maintain accurate records of participant data	2.838	0.898	37
Assist in laboratory analysis, quality control, or data management	2.778	0.637	36
Conduct literature reviews	2.676	0.685	74
Request or acquire equipment or supplies necessary for the project	2.667	0.963	24
Review and edit data to ensure completeness and accuracy of information	2.652	0.714	23
Develop assessment and evaluation tools	2.455	0.800	22
Identify and compile lists of potential research subjects	2.441	0.927	34
Set up, calibrate and maintain laboratory and/or field research equipment	2.286	1.231	21
Prepare materials for submission to granting agencies and foundations	2.238	0.889	21
Derive research questions	2.137	0.732	73
Prepare data collection	2.103	0.765	58
Write and contribute to publications	1.930	0.704	43
Supervise undergraduate students	1.593	0.694	27

N = number of participants that gave answers for the respective task.

be adjusted to consist of trust, motivation, and difficulty. To discuss the model fit of CFA, the criteria of the various model fit indices are considered. It has been argued that RMSEA values less than 0.05 are good, values between 0.05 and 0.08 are acceptable, values between 0.08 and 0.1 are marginal, and values greater than 0.1 are poor [48]. Hence, the RMSEA value of 0.000 in this sample indicates a good fit. The CFI and TLI values are close to 1.00, which depicts a very good fit [49]. The factor of risk is likely to not have contributed to the model due to several possible reasons. First, the items measuring this factor such as ”Failure would result in a substantial negative impact on my life or the lives of others” might not reflect what is considered to be risky in the context of knowledge work, especially in our subgroup of postgraduate students and research associates. It is more likely that not a single task, but a set of events could cause a failure in this context. Second, the tasks examined in this study are likely not indicating of tasks related to high risk. In support of this assumption, Lubars and Tan [17] closely examined tasks having high impact and accountability, such as planning medical treatment for cancer, and showed that this type of tasks is associated with lesser delegability. Consistent with their results, the process component of trust does not significantly contribute to this factor. The other two components, especially trust in machine ability, display high contribution to the factor. This is in line with the previous research about the importance of trust for human-AI collaboration [50, 51, 52]. Task importance, intrinsic motivation, and goals approximately equally contribute to the motivation factor, all three displaying high contribution. Motivation negatively correlates to delegability decision, meaning that humans rather delegate demotivating tasks. Similarly to motivation, difficulty also negatively correlates to delegation, which is consistent with the results of Lubars and Tan [17].

Moreover, results of linear regression further strengthen the implication of the influence of trust on attitude toward AI in collaborative scenarios, such as task delegation, inter alia. The higher the trust, especially trust in machine ability, the higher is the preparedness to delegate a task to AI. Other framework components do not predict delegation on a statistically significant level, which is partly in line with the results of Lubars and Tan [17]. However, this conflicts with previous research. For example, several publications suggest the importance of risk for delegation [53, 54, 55]. More research is needed to reconcile these differences.

The variance explained by the linear regression model (46 %) suggests that there might be other factors not considered by the current framework, that might add to the predictability of delegation decisions. To help shed more light on the topic, future research should study a different population of knowledge workers and look at an extended set of variables.

5.2. Design implications

Participants seem to be equally eager to either act as a human-in-the-loop or be supported by AI in a computer-in-the-loop approach. Across all tasks and participants, 37.15 % chose the computer-in-the-loop approach, while 37.34 % chose the human-in-the-loop approach. In 15.38 % of cases "No delegation" was chosen, while full automation was preferred in only 10.13 % of cases. These findings could support the research stream of hybrid intelligence, which claims that combined approaches of human-in-the-loop and computer-in-the-loop will lead to a much better work performance [8, 5]. Strong preferences for these approaches among knowledge workers should be accounted for in the digitalization of the workplace.

The findings further contribute to the research stream that deals with the design of trustworthy AI, e.g., ([56, 57, 58, 59, 60]) by emphasizing the relevance of trust in task delegability.

Positive association between tasks and delegability implies another design possibility for future workplaces (see Table 4). Tasks such as "Conduct literature reviews", "Maintain accurate records of participant data", and "Assist in laboratory analysis, quality control, or data management" could profit from the computer-in-the-loop approaches. Dealing with large amounts of data and being cumbersome and time-consuming is common to these tasks. Tasks where AI support is welcome are, e.g., "Write and contribute to publications", "Prepare data collection", and "Derive research questions". For most of these tasks, common sense is required, thus it is more appropriate to leverage the human-in-the-loop approach in this case. Tasks predominately basing on human contact, such as "Supervise undergraduate students" seem to have the least benefit from employing AI support. This might be due to the fact that, under current circumstances, participants could not imagine in which way AI could assist them with this task, or due to ethical concerns or strong identification with these tasks. However, with the rapid development of smart assistants [61], this type of task might soon be subject to augmentation with AI.

Finally, understanding delegation decisions of knowledge workers, particularly researchers as well as factors portraying these represents a step further in deriving design knowledge for Human-AI collaboration in knowledge work.

5.3. Limitations and future research

There are a few limitations in our study that should be addressed by future research endeavors on this topic. First, the sample size is relatively small, thus, future studies should increase the sample size to obtain higher statistical power. The suggested minimum sample size for CFA is 100-150 [62, 63], or at least 10 cases per measuring item (140 in our case) [64].

Next, we had unequal sample sizes per task, due to allowing participants to choose for which tasks to provide answers, based on their experience. While this is a disadvantage on the one hand, on the other hand, making questions for all tasks mandatory runs a risk of receiving random answers, or many neutral answers, simply because participants would not know how to honestly answer about something they had no previous experience with.

Further, exploring a wider range of tasks could have led to different insights, especially in terms of the risk factor. Future research could profit from investigating the framework on tasks involving, e.g., making impactful strategic decisions.

Future research could explore the framework in different knowledge work fields and gain valuable insights about its generalizability and different nuances of its applicability. Finally, research on design principles of Human-AI collaboration could account for this framework when investigating different design possibilities.

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