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The Purposeful Presentation of AI Teammates: Impacts on Human Acceptance and Perception

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ABSTRACT

The paper reports on two empirical studies that provide the first examination into how the presentation of an AI teammate's identity, responsibility, and capability impacts humans' perception surrounding AI teammate adoption before interacting as teammates. Study 1's results indicated that AI teammates are accepted when they share equal responsibility on a task with humans, but other perceptions such as job security generally decline the more responsibility AI teammates have. Study 1 also revealed that identifying an AI as a tool instead of a teammate can have small benefits to human perceptions of job security and adoption. Study 2 revealed that the negative impacts of increasing responsibility can be mitigated by presenting AI teammates' capabilities as being endorsed by coworkers and one's own past experience. This paper discusses how to use these results to best balance the presentation of AI teammates' capabilities and responsibilities, as well as identifying AI as teammates.

KEYWORDS

Artificial intelligence; human-AI teaming; AI-teammate design; AI-teammate acceptance

1. Introduction

As Artificial Intelligence (AI) technology progresses in its computational abilities, the technology is beginning to be theorized and observed as more than just a simple tool but rather as a teammate that works interdependently alongside humans (McNeese et al., 2023; O'Neill et al., 2022). The incorporation of AI into human team dynamics poses great potential in future applications, as their computational capabilities outstrip that of humans alone and allows teams to reach highly performative outcomes that are similar, if not greater than, human-only teams (McNeese et al., 2018). Thus, growing research agendas in HCI domains have given attention to the ways in which human perceptions of AI teammates can be measured and accounted for in the design of AI teammates in the hopes of crafting positive perceptions and interactions for acceptance (Khadpe et al., 2020). For example, the graphical presentation of an AI teammate's status can benefit humans' perceived performance and trust of said AI teammate (Schelble et al., 2022c). Despite this growing attention, the vast majority of said studies choose to focus only on perceptions formed during or after human-AI teaming interactions, often ignoring the critical ways in which humans form perceptions of teammates before direct interaction has taken place. Indeed, the perceptions humans hold of any technology prior to its use heavily impact whether humans will want to or will use a novel technology (Davis, 1993; Venkatesh & Bala, 2008) AI, in particular, has been shown to be negatively impacted by its presentation in

media despite humans not having directly interacted but rather observed these technologies (Cave et al., 2018; Szollosy, 2017).

Notably, three potential areas have been shown to impact AI perception during and after interaction, motivating their exploration as factors that impact prior perceptions: (1) identity, (2) responsibility, and (3) capability. Regarding identity, prior work has proposed that presenting AI as tools rather than teammates can potentially improve prior perception (Shneiderman, 2020b), but empirical research has yet to confirm this. For responsibility, the division of labor is a crucial factor in informing perception during interaction (Ghazizadeh et al., 2012; Zhao et al., 2020), but research has not empirically explored the presentation of responsibility prior to interaction with AI. Lastly, the presented capability of AI systems is directly tied to critical perceptions of acceptance (Davis, 1989; Nadarzynski et al., 2019), but the presentation of an AI teammate capability has not been explored prior to interaction with AI teammates. As such, in an effort to increase the perceptions humans have for AI teammates prior to interaction and ensure that human-AI teams form on a positive note, these three factors stand as critical presentation considerations to explore.

We conducted two empirical studies that explored the impact that the presentation of these three factors has on AI teammate perceptions before interaction. In doing so, we explore multiple dimensions of presenting AI teammate identity, responsibility, and capability to answer the following research questions:

- RQ1: How does the presentation of an AI's responsibility, identity, and capability before interacting with humans impact perception?
- RQ1.1: How does the division of responsibility between human and AI teammates impact human perception?
- RQ1.2: How does identifying an AI as a tool or teammate impact human perception?
- RQ1.3: How does the endorsement of an AI teammate's capabilities impact human perception?

This study provides one of the first empirical explorations of how the presentation of prospective AI teammates can impact the perceptions humans form around the adoption of the novel technology. In doing so, this work benefits the HCI domain through two key contributions. First, this research effort is heavily targeted towards using human-derived data to create actionable design recommendations that designers can use to instill positive perceptions of AI teammates that humans want to work with, furthering the cause of human-centered AI in HCI (Xu, 2019). These efforts extend towards the effective presentation of AI systems, and especially AI teammates, which has become an extremely concerning topic in the field of HCI (Rix, 2022; Shneiderman, 2020b). Second, this research helps inform the design of AI teammates that share tasks and responsibilities with humans, which is critical to HCI as the likelihood of AI systems sharing tasks with humans in their daily lives will increase in the near future as AI technology becomes more ubiquitous (Lee, 2020; Schelble et al., 2020). Moving forward, these two contributions will enable both researchers and practitioners to design and present AI teammates in such a way that encourages humans to pursue the formation of human-AI teams.

2. Background: Human-AI teaming and Human-Centered AI

The concept of humans collaborating with machines is not new within the research domain. For decades research has not only theorized how machines could benefit humans (Hoc, 2000; Norman, 1984), but early work in human-machine interaction even theorized how machines themselves could have substantial, teammate-like roles alongside humans (Olson & Sarter, 1998; Robertson, 1996). In practice, this began with humans utilizing simpler automated technologies as tools to enhance efficiency and safety (Boy, 1998; Degani & Heymann, 2002). Within recent years, this concept of human-machine teaming has advanced towards the manifestation of these machine teammates through AI technology due to the computational potential shown by AI (Goetz et al., 2012; Ong et al., 2012). These AI teammates are members of human-AI teams, which have at least one human and one AI member, interdependent roles between team members, and a significant degree of autonomy in decision-making for the artificial teammate as described by O'Neill and colleagues (O'Neill et al., 2023b). The use of AI in human-machine teaming is a step towards fully realizing the term "machine teammate" and comes with several new

considerations and complications given the vast number of expectations the term teammate brings with it, as recent research has already found (McNeese et al., 2023; Zhang et al., 2021). Specifically, the creation of these human-AI teams means that their implementation and design have to revolve around the actual technology that is AI. In other words, AI technology is still relatively new and rapidly advancing, and thus so too is human-AI teaming (National Academies of Sciences, 2021; O'Neill et al., 2023a). While the rapid advancement of AI technology can make it difficult to continuously update an understanding of human-AI teaming, research has intentionally explored both the current state of what human-AI teams are and the future of what human-AI teams could be, often in the same empirical studies (O'Neill et al., 2022). For instance, research has empirically shown how the communication limitations that exist in modern AI systems have an impact on the performative ability of human-AI teams (Demir et al., 2016) and how resolving these limitations would significantly benefit said performative ability (Demir et al., 2015). Even less computational limitations in AI, such as the ever-evolving state of AI ethical behavior, have been examined in how modern ethical limitations can impact human-AI teams (Ramchurn et al., 2021) and how ethical considerations should be ideally considered in human-AI teams (Flathmann et al., 2021). The findings of these studies are critical to this work as they show the criticality of considering not just the ideal of what a human-AI team could be but also the reality of what they are now and how humans perceive them in the modern day.

Addressing the technical and human-centered challenges presented by human-AI teams is necessary and worthwhile, given the benefits of utilizing such teams. Within recent years, research has seen human-AI teams outperform human-human teams and even human experts in a variety of tasks, including remote vehicle survey operations (McNeese et al., 2018) and medical diagnosis (Calisto et al., 2022; Zahedi & Kambhampati, 2021). Generally, the success of these real-world implementations hinges on best utilizing human and AI teammates' unique skills, with medical diagnosis work benefiting from the domain knowledge of humans and the image processing capabilities of AI (Hosny et al., 2018; Lai et al., 2021; Pangal et al., 2022). This benefit can be seen as a merger of human wants and a team's needs, as teams need the computational power of AI to balance with the domain expertise of humans. Beyond present empirical work, research has theorized and outlined multiple other tasks and contexts in which human-AI teaming will readily benefit. Most notably for this study, AI systems are currently being designed to benefit software development teams with AI technology currently showing incredible promise in its ability to aid in the completion of programming tasks (Nguyen & Nadi, 2022; Sobania et al., 2022; Weisz et al., 2021). Moreover, human-AI collaboration has the potential to benefit various other tasks critical to software development, including the modernization (Houde et al., 2022) and documentation (Barenkamp et al., 2020; Wang et al., 2022) of software systems, which are often

repetitive tasks that could be easily completed more rapidly by AI teammates. The above examples demonstrate that the concept of human-AI teaming is not a passing trend but rather a highly appealing application of AI technology that can further optimize modern teaming processes.

However, before human-AI teams can be implemented, AI teammates need to understand how to share work with humans, which enables teams to complete work faster than individuals (Bachrach et al., 2006; Flathmann et al., 2023a). Unfortunately, current research tangential to human-AI teaming has three key limitations that prevent task allocation from being fully understood in human-AI teams. First, research in AI task allocation has been heavily computational and efficiency-minded (Amador et al., 2014; Parasuraman et al., 1996), but effective teammates, and AI teammates, are not wholly reliant on task performance (Crutchfield & Klamon, 2014). Finally, additional human-subjects research in this area examines human perception and performance after they interact with AI or robotic teammates (Flathmann et al., 2023b; Roth et al., 2019; Zhao et al., 2020), but potential task allocation could create negative perceptions in humans that ultimately discourage them from ever interacting with AI teammates, to begin with.

Outside of specifically designing AI teammates, the field of human-centered AI has made critical strides in recent years by designing and verifying general AI systems that collaborate with humans. For instance, past work by Amershi and colleagues outlined multiple guidelines for how to design AI systems that collaborate with humans (Amershi et al., 2019), and these guidelines have gone on to influence a variety of other human-AI research initiatives, including those that explore trustworthy AI systems (Liao et al., 2020; Shneiderman, 2020a) and even creative AI systems (Louie et al., 2020). Importantly, these guidelines and other human-centered considerations have also made their way into human-AI teaming research, with recent human-AI teaming research eliciting the features humans want in their future AI teammates (Zhang et al., 2021). More recent work has even taken the design of human-centered AI teammates a step further by demonstrating how high-performing AI teammates can favor the performance needs of a team to the point that it becomes detrimental to its human teammates (Bansal et al., 2021). This work is an excellent start to designing effective AI teammates, though a significant research gap remains in how to design and present AI teammates that humans are excited to work alongside.

The recent rise in human-AI teaming research is that human teammates presented with an AI teammate tend to have negative perceptions of them (Demir et al., 2018; Musick et al., 2021; Schelble et al., 2022a), which may be the result of human teammates having unclear expectations of the AI teammates abilities or even expectations that are unrealistic given current AI technology (i.e., struggles with natural language processing) (Chowdhary, 2020; Zhang et al., 2021). These negative perceptions can also come with a host of adverse effects on the human-AI team, including reduced trust in the AI teammate (Schelble et al., 2022a), reduced shared understanding (Musick et al., 2021), and

even reduced performance (Schelble et al., 2022b). However, the empirical studies focusing on these perceptual limitations of human-AI teams have all centered around measuring perceptions after the teams have already completed their goal, with none concentrating their study on perceptions before teams have begun. Research has found that the presentation of AI can improve the acceptance of AI by framing itself as a help-seeker and a help-provider and touting the benefits it can provide (Liao & Sundar, 2021). Understanding and overcoming the perceptual problems highlighted here and investigating the proper presentation of an AI teammate are necessary to designing and implementing the best human-AI teams possible, which the current research directly addresses.

The research reviewed here contextualizes the importance of the current study within human-centered AI and HCI research in general. The current research addresses the gaps identified previously in three ways. First, the studies conducted here seek to understand how to overcome all of the perceived limitations that humans have for AI technology (Chowdhury & Sadek, 2012; Gero et al., 2020). Second, this research critically targets the design of AI teammates by exploring how AI presented as a teammate versus a tool affects those same perceived limitations. Finally, research is necessary to understand how the division of responsibility and endorsements of AI capabilities influence the adoption of AI teammates.

3. Study 1: Methods

Study 1 focused on answering RQ1.1 and RQ1.2. Study 1 utilized a factorial survey design, which allows experiments to be conducted through the presentation of vignettes describing scenarios (Auspurg & Hinz, 2014; Jasso, 2006). This has been shown to be an effective methodology to evaluate early human-AI interaction (Li et al., 2022). For RQ1.1, Study 1 examined how the division of responsibility across a single task assigned to both humans and AI can impact human perception (Bachrach et al., 2006; Zhao et al., 2020). For RQ1.2, Study 1 focused on if presenting the identity of an AI as a tool, as opposed to a teammate, can impact human perception, which has been theorized but not empirically confirmed by past research (Shneiderman, 2020b). Study 1 operationalized both of these concepts within the context of human-AI teaming for software development, specifically examining the task of code writing. This operationalization is both justified and relevant for three reasons: (1) human-AI collaboration for code completion is rapidly advancing (Nguyen & Nadi, 2022; Sobania et al., 2022), (2) participants familiar with the domain are more likely to have knowledge of systems like AI, and (3) text completion could be a task completed by either AI teammates or highly skilled AI tools.

3.1. Recruitment and demographics

Participants for this survey were recruited through the Prolific survey distribution platform, which allows rapid and

Table 1. Study 1 demographic information.

Gender							
Male 142	Female 62	Non-Binary 4	Prefer not to say 1	Prefer to Specify 0			
Race							
White 145	Black or African American 21	Latino or Hispanic 8	Asian 20	Native American or Alaskan Native 1	Multicultural 13	Not Specified 1	
Education Level							
High School Graduate 13	Some College 38	Associate's Degree 19	Bachelor's Degree 107	Master's Degree 30	Doctoral Degree 2		

Table 2. Study 1 experimental manipulations, creating a 2x2 experimental design.

Manipulation 1: Responsibility of AI Teammate and Human Teammate (Within)		
Operationalized by % of Code to be Written by Teammate		
Condition #	AI Teammate (%)	Human Teammate (%)
1	5	95
2	20	80
3	35	65
4	50	50
5	65	35
6	80	20
7	95	5

Manipulation 2: Identity of AI Teammate (Between)		
Teammate Label		
Tool Label		

high-quality survey completion. Only participants located in the United States were allowed to complete the survey. Limiting participants to the US, while somewhat of a limitation to generalizability, provided a means of controlling the potential perceptions participants had. To ensure participants' opinions were relevant to the assigned task, the subject pool was limited to individuals who primarily work in software and information technology industries. In total, 214 participants completed the survey, the survey was designed to take 15 minutes to complete, and each participant was paid \$2.63 for completion. Participants were asked three directed attention check questions, which had participants mark a specified answer (Abbey & Meloy, 2017). In total, five participants failed attention checks and were excluded from this study. The average age of participants was 35.80 years old ($SD = 9.30$), and the average survey completion time was 17.02 minutes ($SD = 9.93$). Total demographic information can be found in Table 1.

3.2. Experimental design

The experimental design for this study utilized two manipulations (Table 2). Both of these manipulations and their theoretical underpinnings are described below, and their presentation is described later when describing the presentation and content of the survey itself.

3.2.1. Manipulation 1: AI & human responsibility

The first manipulation for this study, which focused on answering RQ1.1, was the manipulation of responsibility of a singular programming task assigned to either AI or

humans. The theoretical underpinning of this manipulation is derived from research in both AI and teamwork fields. First, AI research has commonly explored the level of autonomy for AI, as higher levels of autonomy often lead to an AI completing more of a task and a human completing less (Parasuraman et al., 2000). Second, the division of labor in teams is critical and teams often have to determine how to best divide labor to best utilize skills, knowledge, and time (Bachrach et al., 2006). In merging these two underpinnings, manipulation 1 was created, which has an AI increase their level of autonomy in a way that directly impacts the workload they are responsible for as well as their human teammate's workload.

Manipulation 1 is a within-subjects manipulation that has seven condition levels. Each level has the AI and human having an increasing and decreasing amount of responsibility on a singular task, respectively. This is operationalized as the AI being responsible for X% of a code writing task and the human be Y% responsible, with X and Y summing to 100%. It was chosen to present this manipulation in a within-subjects manner to allow humans to better differentiate and compare the potential divisions of responsibility. Pilot testing was performed to ensure humans distinguished these condition levels.

3.2.2. Manipulation 2: AI identity

The second manipulation of this work, which centers around RQ1.2, examines the impacts that identifying an AI as a teammate or tool can have on perception. This manipulation is derived from past work that has theorized that the teammate identity will negatively impact human perception due to teammates having higher expectations than tools (Shneiderman, 2020b). However, the teammate identity can be a benefit too as it could signal to humans that they will be interdependent and collaborative with this AI (O'Neill et al., 2022). As such, manipulation 2 examines if the simple identification of an AI teammate can impact human perception due to these expectations. Manipulation 2 is a between-subjects manipulation with two conditions.

3.3. Procedure & survey Structure

The individual steps within the provided survey are detailed below. Before larger data collection, this survey was initially piloted twice. The first round of piloting was used to increase the visibility of the manipulations, which resulted

in minor changes being made. The second round of piloting ensured the survey was technically reliable.

3.3.1. Informed consent & Pre-Surveys

Upon clicking the survey link, participants were immediately provided with an informed consent letter that could be agreed to at the bottom. Then, participants completed a variety of pre-surveys, including demographics, job domain identification, and some individual differences surveys, which are not the focus of this article.

3.3.2. Introduction of AI

After these pre-surveys, the survey introduced participants to the context of the task and the AI that would be helping them with the task. This introduction simply told participants they would be working with an AI to complete a software development task. This description was intentionally left open-ended to allow participants to form their own expectations simply based on the identity proscribed to the AI teammate or tool.

3.3.3. Vignette Structure

Given that manipulation 1 of this study was a within-subjects manipulation, this study presented seven vignettes to participants, one for each condition level. These vignettes contained a brief reminder of the context, a table that told participants how much of the code they and their AI were responsible for, and five, 7-point Likert-style questions (detailed below). The structure of these vignettes stayed consistent across all seven with only minor content changes being made based on the assigned manipulations (detailed below). For readability and reproducibility purposes, the vignette used for study 1 has been recreated as **Table A1** in the Appendix.

3.3.4. Operationalization of manipulations

The manipulations for this study were operationalized through text-based changes in the survey. Manipulation 1 was operationalized by changing the values presented in the table within each vignette based on the condition levels shown in **Table 2**.

Manipulation 2 occurred during both the introduction of the AI and within each vignette. When introducing the AI, it was introduced as either a teammate or tool, but no other information in the introduction was changed based on the identity. Within the vignettes, the AI was either referred to as a tool or a teammate. Additionally, given that this study is focused on adoption and acceptance, language in survey questions and the vignettes also differed based on the condition to ensure that verbiage was appropriate for the chosen identity. Specifically, participants were asked if they would “use” the “tool” in their team or “accept” the “teammate” into their team. Assignment of a manipulation 2 condition was randomized between participants through weighted randomization.

3.3.5. Individual vignette Measures

Each within-subjects vignette was accompanied by five questions, and these questions were designed based on factors that are critically important to both the adoption of new technology and the hiring of new teammates. The specific questions asked along with the research used to derive said questions can be found in **Table 3**.

4. Study 1: Results

The following results are organized based on the five measurements taken in the factorial survey vignettes. Given that shared responsibility both exists and is operationalized as a spectrum, analysis leveraged linear mixed effects modeling to explore how the gradual shift in shared responsibility changes perception (RQ1.2). Moreover, this methodology will enable the impact of teammate identity to be explored both as a main effect and interaction effect, in turn showing the main impact identity has (RQ1.1) and the holistic impact identity and responsibility have on perception (RQ1). Also, given the single-item measures used, a cumulative link mixed model, which is a robust form of a linear mixed model, has been used to ensure statistical validity. Note that models that contain non-significant effects will be reported, but the model used for the analysis of fixed effects will be noted in each table.

4.1. Capability of AI teammate or tool to complete responsibility

For participants’ perceived capability of the AI system, we first ran a model with only a random intercept, and then added the responsibility level of the AI, the identity of the AI (teammate vs. tool), and their interaction. The responsibility of the AI significantly improved the linear model created for participants’ perception of AI capability, but the effect of identity and the interaction effect between responsibility and identity did not significantly improve the model (**Table 4**). Analysis of the selected model’s fixed effects revealed a significant effect of responsibility ($\beta = -.28$, $t(1252) = 10.33$, $SE = .03$, $p = <.001$) on perceived capability. The effect size of responsibility ($d = .58$) denotes a medium effect size. **Figure 1** shows that with increased responsibility for the AI, participants tend to increasingly doubt its ability to actually fulfill the task.

4.2. Potential helpfulness of AI teammate or tool

The responsibility of the AI significantly improved the linear model created for potential AI helpfulness, but the effect was found to be quadratic, which means both a linear representation of responsibility and a squared representation of responsibility are included in the significant model (**Table 5**). Additionally, neither the effect of identity nor the interaction effect between responsibility and identity significantly improved the model (**Table 5**). Analysis of the selected model’s fixed effects revealed a significant effect of responsibility ($\beta = 0.648$, $t(1252) = 5.34$, $SE = .12$, $p = <.001$) and squared

Table 3. Post-Scenario questions shown after each vignette. Questions were provided a seven-point Likert scale, Strongly disagree ⇔ Strongly Agree.

Post-Scenario Questions		Research Relevance
Measurement Factor	Question	
Capability of AI	I think the AI [Tool, Teammate] would be capable of performing these responsibilities.	Perceived Performance (Liu & Ma, 2006)
Helpfulness of AI	If I were to [use, accept] the AI [Tool, Teammate], it would be helpful to my team.	Perceived Utility (Davis, 1989)
Helpfulness of Self	If I were to [use, accept] the AI [Tool, Teammate], my teammates would still benefit from my skillset.	Employability (Bhargava et al., 2021)
Job Security	If my team were required to [use, accept] the AI [Tool, Teammate], I would feel concerned for my job security. (Reverse Coded)	Job Security (Bhargava et al., 2021)
Adoption Likelihood	I would be likely to [use, accept] the AI [Tool, Teammate].	Intent to Use (Davis, 1989)

Table 4. Linear model for effects of conditions on perceived capability of AI to complete workload. Each model is built upon and compared to the one listed above it.

Model	$\Delta\chi^2$	Δdf	p-value
Perceived Capability ~ (1—pid)			
* + AI Responsibility	110.40	1	<.001
+ Identity	.04	1	.836
+ AI Responsibility:Identity	.43	1	.513

*Denotes model used for analysis of fixed effects.

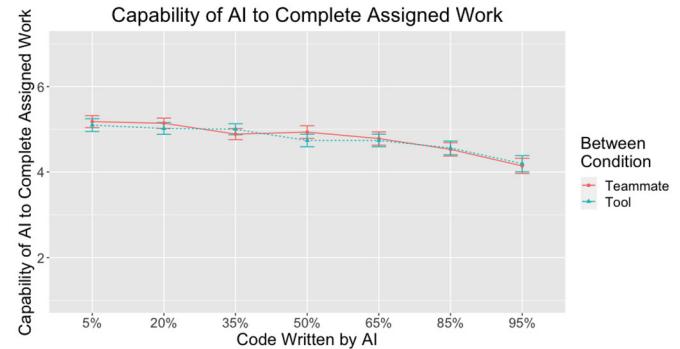
responsibility ($\beta = -.08$, $t(1252) = 5.61$, $SE = .01$, $p = <.001$) on perceived helpfulness. The effect size of responsibility ($d = .30$) and squared responsibility ($d = .32$) reflect a medium effect size for each (Cohen, 2013). Figure 2 shows that the perceived helpfulness of an AI is lowest when the AI has very little responsibility, increases when the AI tool shares between 20% and 50% of the responsibility, and drops down again when its responsibility increases further. However, despite this trend, perceived helpfulness generally stays positive throughout increasing levels of responsibility.

4.3. Potential helpfulness of self alongside AI teammate or tool

The responsibility of the AI significantly improved the linear model created for the potential helpfulness of one's self, and the effect of identity did not significantly improve the model. However, the interaction effect between responsibility and identity did significantly improve the model (Table 6). Analysis of the selected model's fixed effects revealed a significant main effect of responsibility ($\beta = -.78$, $t(1252) = 17.34$, $SE = .04$, $p = <.001$) and a significant interaction effect ($\beta = 0.12$, $t(1252) = 2.18$, $SE = .05$, $p = <.030$) on the perceived benefit of self with a large ($d = 0.98$) and small ($d = 0.12$) effect size, respectively (Figure 3).

4.4. Job security alongside AI teammate or tool

Both responsibility of the AI and the identity of the AI significantly improved the model, but the interaction effect did not (Table 7). Analysis of the selected model's fixed effects revealed a significant effect of responsibility on job security ($\beta = -.83$, $t(1252) = 24.27$, $SE = .03$, $p = <.001$). Additionally, the effect of identity was significant ($\beta = -.73$, $t(207) = 2.15$, $SE = .34$, $p = .03$) for participants' job security as well. The effect size of responsibility ($d = 1.37$) reveals a large effect size, while the

**Figure 1.** Figure of capability of AI system to complete responsibility based on responsibility and identity. Error bars denote 95% confidence interval.

effect size of identity ($d = .30$) denotes a medium effect size (Cohen, 2013). Figure 4 shows that participants perceived less job security when an AI is assigned a larger proportion of the responsibility and perceived job security is higher when the AI is identified as a tool rather than a teammate. Examining Figure 4 one can see that as AI responsibility increase, perceived job security actually goes from being a positive perception to a fairly negative perception of job security on the 7-point scale.

4.5. Likelihood to accept/adopt AI teammate or tool

The linear and quadratic effect of responsibility of the AI teammate significantly improved the adoption likelihood model, but the identity did not significantly improve the model (Table 8), but the interaction between linear responsibility and identity did significantly improve the model (Table 8). Analysis of the selected model's fixed effects revealed a significant linear effect ($\beta = 0.47$, $t(1251) = 3.72$, $SE = .13$, $p = <.001$) and squared effect ($\beta = -.09$, $t(1251) = 6.04$, $SE = .01$, $p = <.001$) of responsibility on adoption likelihood showing that as the AI is assigned more responsibility adoption likelihood rises, but then falls off as responsibility more heavily favors AI over humans. Additionally, the linear effect of responsibility and identity had a significant interaction effect on adoption likelihood ($\beta = -.13$, $t(1251) = 2.55$, $SE = .05$, $p = .011$), showing that the difference between the tool condition and the teammate condition in terms of likelihood increases in favor of the tool condition when the AI is assigned more responsibility. The effect size (Cohen's d) of responsibility level ($d = .21$)

Table 5. Linear model for effects of conditions on potential helpfulness. Each model is built upon and compared to the one listed above it.

Model	$\Delta\chi^2$	Δdf	p-value
Helpfulness of AI ~ (1—pid)			
+ AI Responsibility	.47	1	.493
* + AI Responsibility ²	31.70	1	<.001
+ Identity	.75	1	.586
+ AI Responsibility : Identity	1.41	1	.235
+ AI Responsibility ² : Identity	.12	1	.732

*Denotes model used for analysis of fixed effects.

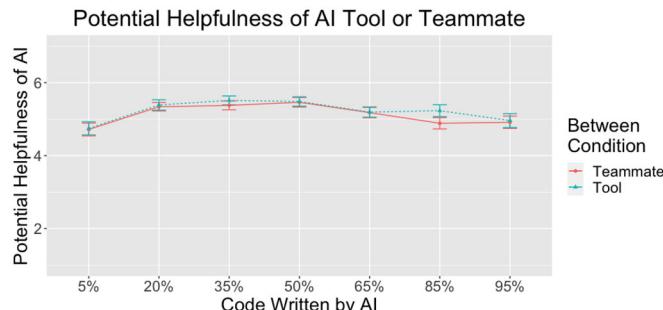


Figure 2. Graph of potential helpfulness of AI based on responsibility and identity. Error bars denote 95% confidence interval.

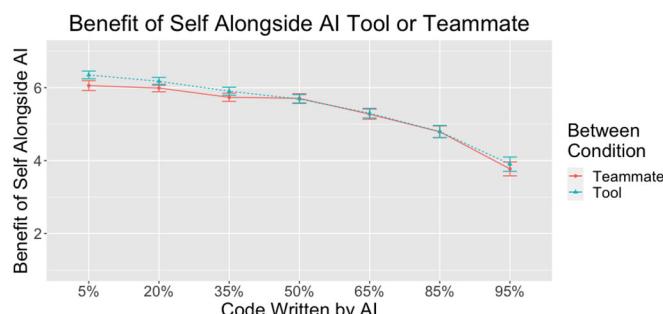


Figure 3. Graph of the potential benefit of self alongside AI system based on responsibility and identity. Error bars denote 95% confidence interval..

Table 6. Linear model for effects of conditions on one's own perceived benefit. Each model is built upon and compared to the one listed above it.

Model	$\Delta\chi^2$	Δdf	p-value
Helpfulness of Self ~ (1—pid)			
+ AI Responsibility	571.09	1	<.001
+ Identity	.51	1	.473
* + AI Responsibility:Identity	4.76	1	.029

*Denotes model used for analysis of fixed effects.

Table 7. Linear model for effects of conditions on job security. Each model is built upon and compared to the one listed above it.

Model	$\Delta\chi^2$	Δdf	p-value
Job Security ~ (1—pid)			
+ AI Responsibility	758.94	1	<.001
* + Identity	4.57	1	.03
+ AI Responsibility:Identity	.06	1	.800

*Denotes model used for analysis of fixed effects.

and squared responsibility (0.34) signals a medium effect size, while the effect size of the interaction ($d = .13$) indicates a small effect size. **Figure 5** shows that humans' adoption likelihood first increases as AI gains more responsibility, but generally declines as the AI is assigned demonstrably more responsibility.

Job Security Perceived with AI Tool or Teammate

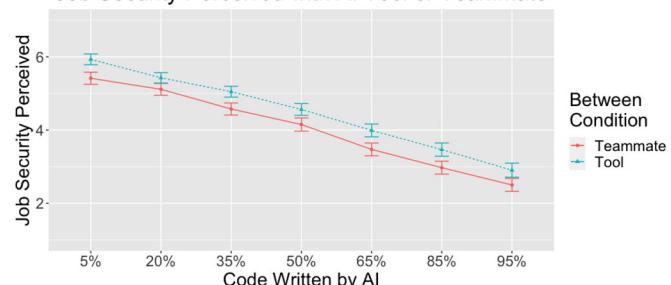


Figure 4. Figure of job security when working with AI based on responsibility and identity. Error bars denote 95% confidence interval.

Table 8. Linear model for effects of conditions on likelihood to adopt. Each model is built upon and compared to the one listed above it.

Model	$\Delta\chi^2$	Δdf	p-value
Adoption Likelihood ~ (1—pid)			
+ AI Responsibility	151.22	1	<.001
+ AI Responsibility ²	36.36	1	<.001
+ Identity	2.14	1	.143
* + AI Responsibility : Identity	6.52	1	.011
+ AI Responsibility ² : Identity	1.52	1	.218

*Denotes model used for analysis of fixed effects.

4.6. Summary of Study 1 results

Study 1's results paint an intriguing picture of how the responsibility AI systems are assigned is far more important than the way they are identified. While the effects of AI system responsibility were significant for every single perception measured, the identity only significantly impacted one's own perceived helpfulness, job security, and adoption, but even those effects had a small effect size compared to AI responsibility, making it less of a concern.

An interesting juxtaposition concerns adoption likelihood and helpfulness to the rest of the measurements. One might assume these measurements to follow similar trends; however, adoption likelihood and helpfulness follow quadratic trends where they are highest when humans and AI share similar levels of responsibility, but other measures generally trend downwards and are at their highest when AI responsibility is at its lowest. Additionally, we see that AI systems assigned large portions of shared work can create job security concerns and internal doubts about one's own helpfulness, even if humans feel skeptical about the AI system's ability to fully accomplish its responsibility. Additionally, we see that while the helpfulness of an AI teammate declines as responsibility increases, they stay relatively positive, but adoption likelihood and job security consistently drop to relatively neutral and negative perceptions, respectively.

5. Study 2: Methods

While Study 1 focused on responsibility and identity, Study 2 turns its focus toward how to present the capabilities of AI teammates to better human perception. Study 2 differed in two key ways from Study 1. First, Study 2 furthered the understanding of RQ1.1 by examining shared responsibility across multiple tasks, which is likely to occur in future human-AI teams (Liu & Zhao, 2021; R. Jay et al., 2016).

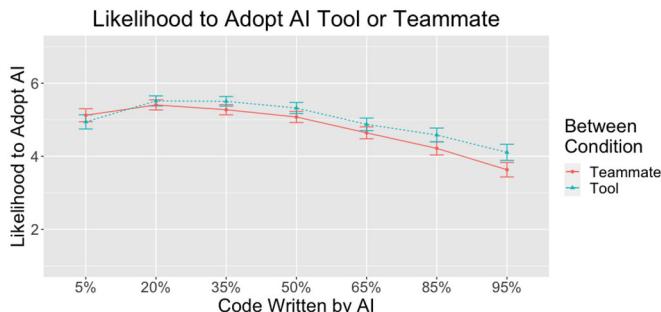


Figure 5. Graph of likelihood to adopt AI based on teammate responsibility and identity. Error bars denote 95% confidence interval.

Second, Study 2 focused on RQ1.3 by examining how presenting an AI teammate's capability through various endorsements could impact human perception.

5.1. Recruitment

Recruitment procedures were similar to Study 1: the Prolific survey platform was used, participants were restricted to the United States, and the subject pool was limited to those who work in industries related to software and information technology. In total, 303 participants completed the survey, the survey was designed to take 20 minutes, and each participant was paid \$3.50 for survey completion. Multiple attention checks were administered during the survey. In total, six participants failed attention checks or completed the survey in an unreasonably short time and were excluded from this study. The average age of participants was 33.59 years ($SD = 10.04$), and the average survey completion time was 20.44 minutes ($SD = 36.84$). Further demographic information can be found in [Table 9](#).

5.2. Experimental design

Similar to Study 1, Study 2 leverages two different manipulations, and these manipulations work to extend the results of Study 1 ([Table 10](#)).

5.2.1. Building on Study 1

Notably, Study 1 found that identifying AI as a tool over teammate benefited perception, and increasing singular-task responsibility demonstrably decreased worsened perceptions. Study 2 builds on these findings by first understanding if multi-task shared responsibility follows a similar trend to singular-task shared responsibility, both of which are common in teams. Given the findings of Study 1, it would be expected that negative effects remain and potentially grow stronger in multi-task environments due to a further increase of AI responsibility within a team. Second, Study 1 found that referring to AI as a tool benefited perception, but that does not mean that AI teammates will not exist and be presented to users in the future. In turn, Study 2 explores alternative ways to boost the perceptions of AI teammates prior to interaction without having to remove their status as a teammate. As such, this work can better identify robust

ways of increasing the perceptions of AI teammates specifically. In exploring these extensions, Study 2 leverages 2 unique manipulations ([Table 10](#)).

5.2.2. Manipulation 1: AI teammate responsibility

Study 2 presented this responsibility in the form of multiple shared tasks as opposed to a single shared task ([Table 10](#)). This manipulation is still supported by AI research into the levels of autonomy, which can have AI systems perform more functions as they increase in autonomy (Parasuraman et al., 2000), but this update also provides a critical teaming consideration as teammates often have to interdependently share tasks to complete a shared goal (Saavedra et al., 1993). Similar to Study 1, manipulation 1 utilized a within-subjects design where each participant was provided with each condition level. Importantly, humans were also told they would be responsible for monitoring the performance of the AI teammate as it would be unrealistic to fully remove the human from the equation (Jarrahi, 2018).

5.2.3. Manipulation 2: AI teammate endorsement

Manipulation 2 for this study is specifically concerned with the presentation of an AI teammate's capabilities. Specifically, this presentation is done through the concept of endorsements, where an aspect of the AI teammate is explicitly endorsed. This manipulation was a between-subjects condition with six condition levels, each of which has its own theoretical derivation from the literature. The specific condition levels and derivations can be found in [Table 10](#).

5.3. Procedure

Study 2's survey followed a fairly similar procedure to that of Study 1, and these differences are discussed below. Study 2 was also piloted in a similar way to Study 1.

5.3.1. Informed consent & Pre-Surveys

The informed consent and pre-survey process for Study 2 followed a fairly identical structure to Study 1. The only notable difference is that the informed consent letter was updated to reflect the correct time commitment for Study 2.

5.3.2. Introduction of the AI teammate

Given that the manipulations changed from Study 1 to Study 2, the introduction of AI also changed. First, the AI was always introduced as a teammate. Second, participants were told that the AI teammate would be tasked with helping complete a list of software development tasks.

5.3.3. Vignette Structure & manipulations

The vignettes for Study 2 were fairly similar to that of Study 1. The main difference was the presentation of the manipulations. First, the AI was always presented as a teammate in these vignettes. Second, the presentation of responsible,

Table 9. Study 2 demographic information.

Gender				
Male 191	Female 103	Non-Binary 3	Prefer not to say 0	Prefer to Specify 0
Race				
White 199	Black or African American 27	Latino or Hispanic 16	Asian 26	Native Hawaiian or Pacific Islander 1
Education Level				
High School Graduate 22	Some College 46	Associate's Degree 28	Bachelor's Degree 158	Master's Degree 41

Table 10. Study 2 experimental manipulations create a 6x7 design.

Software Developer Responsibilities		
Task #	Task Description	
1	Checking Code for Spelling Errors and Typos	
2	Checking Code for Logic Errors	
3	Writing Code Inside Designed Function Blocks	
4	Designing Code Based on a Software Development Plan	
5	Creating a Software Development Plan Based Off of Written Requirements	
6	Creating Written Requirements Based on Client Interviews	
7	Interviewing Clients about the Requirements of the Software	
8	Overseeing AI Teammate (Not Presented Until Vignette)	
Manipulation 1: AI Responsibility (Within)		
	AI Completes Task 1	
	AI Completes Tasks 1 & 2	
	AI Completes Tasks 1, 2, & 3	
	AI Completes Tasks 1, 2, 3, & 4	
	AI Completes Tasks 1, 2, 3, 4, & 5	
	AI Completes Tasks 1, 2, 3, 4, 5, & 6	
	AI Completes Tasks 1, 2, 3, 4, 5, 6, & 7	
Manipulation 2: AI Capability Endorsement (Between)		
Condition Label	Description	Related Factor
None	No bullet point list provided	Control
Coworker Endorsed	List of endorsements made by coworkers that focus on how AI teammates help their team	External Social Influence (Venkatesh & Davis, 2000)
Expert Endorsed	List of endorsements made by researchers that focus on the workplace improvements	External Social Influence (Venkatesh & Davis, 2000)
Past Performance	List of technical capabilities and task performance rates of the AI teammate	Capability Communication (Amershi et al., 2019)
Previously Observed	First hand observations on the how helpful the AI teammate is to other teams	First Hand Experience (Amershi et al., 2019)
Human Override	List of ways that humans can override the actions and behaviors of their AI teammate if they see fit	Feeling of Control (Venkatesh & Bala, 2008)

while still a table, now listed each task assigned to the AI and each task assigned to the human. Finally, at the end of each vignette before the questions were presented, manipulation 2 was provided. Manipulation 2 was provided through a one-sentence endorsement of the AI teammate followed by three bullet points that further elaborated this statement. Participants were assigned their condition for manipulation 2 when first opening the survey, and they retained the same condition for each vignette presented. For an example vignette, please refer to the visual representation in Table A2 in the Appendix.

5.3.4. Individual vignette Measures

The questions provided at the end of each vignette within Study 2 mirrored those provided in Study 1 for participants in the teammate condition. Please refer back to the prior methods section for a full explanation of each question provided.

6. Study 2: Results

Similar to Study 1, cumulative link mixed modeling was used to analyze the results of Study 2. This will further allow shared responsibility to be viewed as a spectrum rather than isolated levels, increasing our understanding of shared responsibilities' effects on perception (RQ1.2). Moreover, capability endorsements can be transformed into dummy variables alongside the control, which will explore how capability directly impacts perception (RQ1.3) and how capability and responsibility presentation combine to influence perception (RQ1).

6.1. Capability of AI teammate to complete responsibility

For participants' perceived capability of an AI teammate, the responsibility assigned to the AI teammate and the interaction between responsibility and capability endorsement

Table 11. Linear model for effects of responsibility and capability endorsement on capability of AI teammate. Each model is built upon and compared to the one listed above it.

Model	$\Delta\chi^2$	Δdf	p-value
Capability ~ (1—pid)			
+ AI Responsibility	705.01	1	<.001
+ Capability Endorsement	7.79	5	.168
* + AI Responsibility : Capability Endorsement	18.30	5	.003

*Denotes model used for analysis of fixed effects.

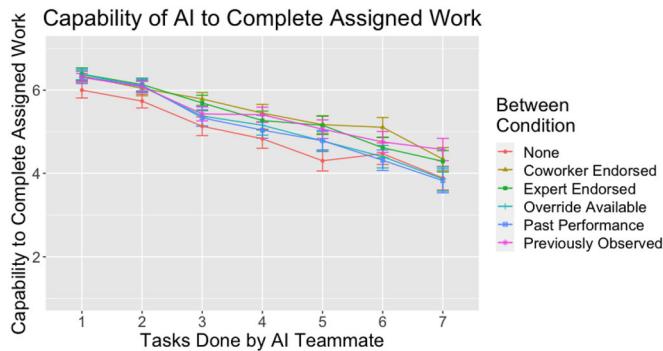


Figure 6. Graph of AI capability based on teammate responsibility and capability endorsement. Error bars denote 95% confidence interval.

Table 12. Table of the selected model's significant fixed effects. Main effects are listed regardless of significance if a relevant interaction effect is present.

Factor	β	SE	df	t	p-value	Cohen's d
AI Responsibility	-.61	.05	1776	11.34	<.001	.54
Expert Endorsed	1.13	.52	291	2.15	.032	0.25
Human Override	1.03	.55	291	1.89	.059	0.22

significantly improved the linear model (Table 11). Analysis of the final model's fixed effects revealed a significant effect of responsibility on perceived capability (Table 12)—a similarly negative trend (Figure 6) to that shown in Study 1. Fixed effect analysis revealed that no single capability endorsement method significantly improved perceived capability or significantly mitigated the negative effect of increased responsibility (Table 12). Due to the significant interaction effect, the main effects of endorsement were included, and expert endorsements and override capabilities were shown to have significant and near-significant effects, respectively (Table 12). An analysis of the interaction effect revealed that no single effect was significant, but past performance reporting and override capabilities neared significance (Table 12).

6.2. Potential helpfulness of AI teammate

For the perceived helpfulness participants saw in the AI teammate, the responsibility assigned to the AI teammate, and the interaction effect between responsibility and capability endorsement was significant (Table 13). An analysis of the fixed effects revealed that unlike Study 1, helpfulness generally demonstrated a downward linear trend rather than a quadratic relationship with AI teammate helpfulness (Figure 7), suggesting that humans may have different preferences when sharing multiple tasks with AI teammates as opposed to a singular task (Table 14). The significant interaction

Table 13. Linear model for effects of responsibility and capability endorsement on the helpfulness of AI teammate. Each model is built upon and compared to the one listed above it.

Model	$\Delta\chi^2$	Δdf	p-value
Helpfulness of AI ~ (1—pid)			
+ AI Responsibility	126.74	1	<.001
+ Capability Endorsement	7.71	5	.173
* + AI Responsibility : Capability Endorsement	20.42	5	.001

*Denotes model used for analysis of fixed effects.

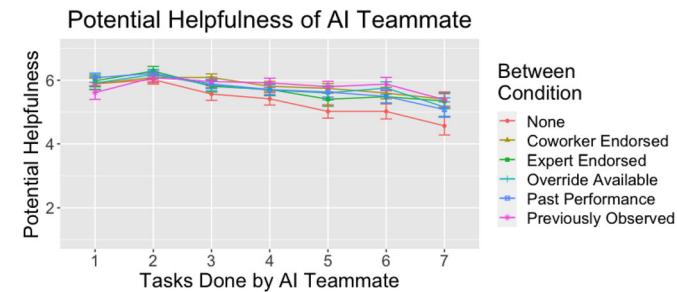


Figure 7. Graph of the helpfulness of AI based on teammate responsibility and capability endorsement. Error bars denote 95% confidence interval.

Table 14. Table of the selected model's significant fixed effects. Main effects are listed regardless of significance if a relevant interaction effect is present.

Factor	β	SE	df	t	p-value	Cohen's d
AI Responsibility	-0.40	.05	1776	7.50	<.001	.36
Coworker Endorsed	-.03	.49	291	.06	.955	-0.01
Previously Observed	-.38	.49	291	.78	.438	0.09
Human Override	.03	.51	291	.07	.948	0.01
AI Responsibility:Coworker Endorsed	.19	.08	1776	2.46	0.014	.29
AI Responsibility:Previously Observed	.32	.08	1776	4.26	<.001	.50
AI Responsibility:Human Override	.16	.08	1776	2.01	.044	.24

effects demonstrate that coworker endorsements, previous observations, and the ability to override the AI teammate all significantly mitigate the negative effect of increasing responsibility, with previous observations having the strongest effect of $d = .22$, which almost completely overcomes the negative effect of increased responsibility (Table 14). This effect shows that AI teammates are perceived as being less helpful when they are assigned more work, but that AI teammates can be seen as helpful despite a greater level of responsibility when humans have observations with the AI teammate.

6.3. Helpfulness of self alongside AI teammate

For perceived helpfulness of one's self, the responsibility assigned to the AI teammate and the interaction effect between responsibility and capability endorsement significantly improved the model (Table 15). Analysis of the selected model's fixed effects revealed a similar trend to Study 1, where increases in AI teammate responsibility result in decreases in the perceived helpfulness of one's self alongside said AI teammate (Table 16). Additionally, override capabilities had a significant and positive main effect, and coworker endorsements also had a significant and positive interaction effect. These results indicate that one's perceived helpfulness of themselves is largely driven by shared responsibility, but minor benefits can be made to these

Table 15. Linear model for effects of responsibility and capability endorsement on the helpfulness of one's self. Each model is built upon and compared to the one listed above it.

Model	$\Delta\chi^2$	Δdf	p-value
Helpfulness of Self \sim (1—pid)			
* + AI Responsibility	806.24	1	<.001
+ Capability Endorsement	8.04	5	.154
+ AI Responsibility : Capability Endorsement	17.44	5	.003

*Denotes model used for analysis of fixed effects.

Table 16. Table of the selected model's fixed effect of responsibility on helpfulness of self.

Factor	β	SE	df	t	p-value	Cohen's d
AI Responsibility	-.71	.06	1776	12.83	<.001	0.61
Coworker Endorsed	-0.40	.48	291	.82	.410	0.10
Human Override	1.32	.52	291	2.57	.011	.30
AI Responsibility:Coworker Endorsed	.20	.08	1776	2.55	.011	.12

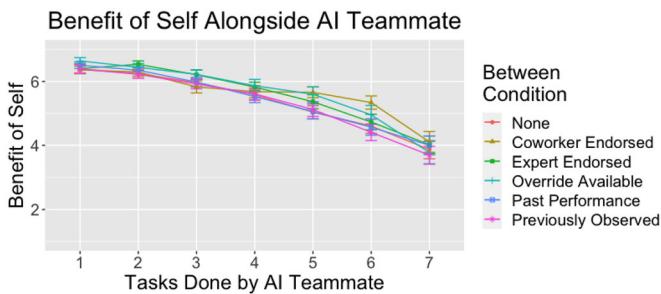


Figure 8. Graph of the helpfulness of self based on teammate responsibility and capability endorsement. Error bars denote 95% confidence interval.

Table 17. Linear model for effects of responsibility and capability endorsement on job security. Each model is built upon and compared to the one listed above it.

Model	$\Delta\chi^2$	Δdf	p-value
Job Security \sim (1—pid)			
* + AI Responsibility	907.84	1	<.001
+ Capability Endorsement	10.43	5	.063
+ AI Responsibility : Capability Endorsement	10.68	5	.058

*Denotes model used for analysis of fixed effects.

perceptions through override capabilities and coworker endorsements (Figure 8).

6.4. Job security concerns created by AI teammate

For participants' perceived job security, the responsibility assigned to the AI teammate significantly improved the model, but the main effect of endorsement and the interaction effect neared but did not reach significance (Table 17). Analysis of the selected model's fixed effects revealed that as the responsibility of the AI teammate increases, participants' job security was heavily affected in a negative way (Table 18). These results demonstrate that perceived job security is heavily predicated on the division of responsibility with an AI teammate's capabilities having very little if any influence over these perceptions prior to interaction (Figure 9).

6.5. Likelihood to adopt AI teammate

For participants' likelihood to adopt the AI teammate, the workload assigned to the AI teammate, the capability

Table 18. Table of the selected model's fixed effects of responsibility and capability endorsement on job security. Effect size is only shown for significant effects.

Factor	β	SE	df	t	p-value	Cohen's d
AI Responsibility	-.74	.03	1781	27.00	<.001	1.28

Job Security Perceived with AI Teammate

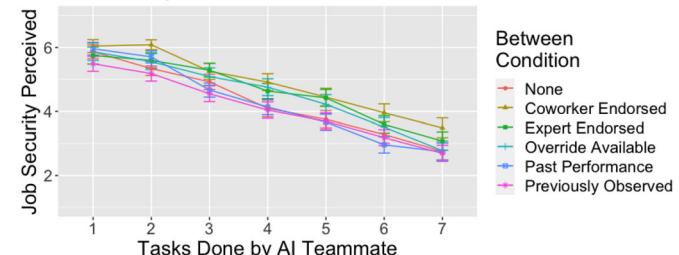


Figure 9. Graph of job security based on teammate responsibility and capability endorsement. Error bars denote 95% confidence interval.

Table 19. Linear model for effects of responsibility and capability endorsement on likelihood to adopt. Each model is built upon and compared to the one listed above it.

Model	$\Delta\chi^2$	Δdf	p-value
Adoption Likelihood \sim (1—pid)			
* + AI Responsibility	601.96	1	<.001
+ Capability Endorsement	10.81	5	.055
* + AI Responsibility : Capability Endorsement	30.30	5	<.001

*Denotes model used for analysis of fixed effects.

Table 20. Table of the selected model's fixed effects of responsibility, capability endorsement, and interactions on adoption likelihood. Effect size is only shown for significant effects.

Factor	β	SE	df	t	p-value	Cohen's d
AI Responsibility	-.68	.06	1776	12.35	<.001	.59
Coworker Endorsed	.17	.51	291	.33	.755	0.04
Past Performance	.99	.50	291	1.97	.049	0.11
Previously Observed	-.16	.50	291	.32	.749	0.04
AI Responsibility:Coworker Endorsed	.22	.08	1776	2.88	.004	.14
AI Responsibility:Previously Observed	.26	.08	1776	3.40	<.001	.16

endorsement of said AI teammate and the interaction between these two features significantly improved the linear model (Table 19). Analysis of the final model's fixed effects revealed a significant negative effect of increasing the AI's responsibility on adoption likelihood in the control condition (Table 20), which signals a similar negative trend to that shown in Study 1. Having a prior observation of the AI teammate provided a significant and positive main effect (Table 20). Additionally, coworker endorsements and previous observations of the AI teammate were able to significantly mitigate (but not fully overcome) the negative effect of increasing the AI's responsibility (Table 20). Similar to Study 1, these results show how the likelihood for humans to adopt an AI teammate decreases as said AI teammate is assigned a greater responsibility (Figure 10).

6.6. Summary of Study 2 results

The results of Study 2 tell a similar story to those of Study 1: increasing the responsibility of a prospective AI teammate

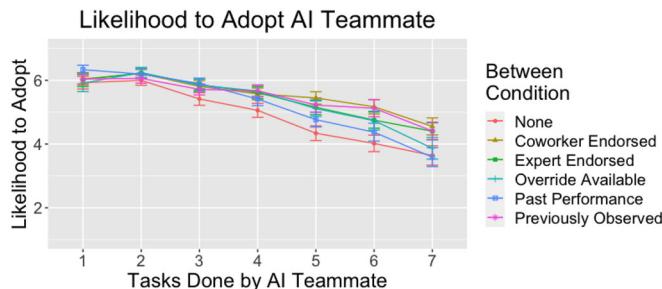


Figure 10. Graph of likelihood to adopt AI based on teammate responsibility and capability endorsement. Error bars denote 95% confidence interval.

negatively affects human perception. Moreover, Study 2 revealed that this effect transcends singular tasks and applies to the division of workload across multiple tasks as well. However, Study 2 also revealed that these declining effects can be somewhat mitigated through the endorsement of an AI teammate's capabilities. Specifically, coworker endorsements and having a prior observation of the prospective AI teammate consistently showed the strongest improvement of the perceptions measured. This finding signals the importance of having observed AI teammates before bringing them into a team, and that observations can either come from oneself or from a coworker in a similar setting. However, the most interesting outcome of this effect is similar to that of Study 1, where job security decreases with increased responsibility at a much faster rate than perceived capability and helpfulness. This suggests that the concerns humans have for their job security are not coming from a fear that their AI teammate will be so highly skilled that they themselves become obsolete, but rather from a reflection upon the (arguably institutionally mandated) role said AI teammate is going to occupy in their team despite its abilities.

7. Discussion

This research's results demonstrate the spectrum of human perception based on the presentation of prospective AI teammates. This spectrum details the potential positives and negatives that have to be considered when designing an AI teammate for real-world teams. Furthermore, the current study's experiments explored if the presentation of an AI teammate's capabilities could mitigate these effects to allow prospective AI teammates to have a greater level of responsibility. Going back to the proposed research questions of this study, these results are leveraged by the following discussion to inform the presentation of AI teammates' responsibility and capability (RQ1.2 and RQ1.3) as well as provide an interesting exploration of the appropriateness of identifying AI as teammates (RQ1.1).

7.1. Balancing human teammates' needs and wants for AI teammates

The results of this work show that designing the ideal responsibility and capability presentation (RQ1.2 and RQ1.3, respectively) of AI teammates requires a nuanced and

holistic approach. For example, if one were to solely look at the adoption likelihood and perceived helpfulness of the AI in Study 1, RQ1.2's answer would be that AI teammates should also have similar levels of responsibility compared to their human teammates. However, examining the results of job security would denote that the answer to RQ1.2 would be to always minimize the amount of responsibility given to an AI teammate. In reality, RQ1.2 and RQ1.3 do not have entirely consistent answers, as the result differences between Study 1 and Study 2 demonstrate that ideal levels of responsibility vary based on the types of tasks that human and AI teammates share responsibility over. As such, the following discussion leverages two results, the difference between job security and other perceptions in Study 1 and the impact of capability endorsements from Study 2, to provide guided paths toward answering RQ1.2 and RQ1.3, respectively.

For RQ1.2, different conclusions can be made if one looks at either adoption likelihood or job security in isolation of each other. These findings show a trend that exists within HCI, which is that the potential needs and wants of humans may not entirely align (Kramer et al., 2000; Oudshoorn & Pinch, 2003). For instance, for the sake of job security, humans may want to minimize the amount of responsibility provided to an AI, but humans also recognize that AI teammates with a somewhat even amount of shared responsibility to them are more helpful. Thus, answering RQ1.2 would create an impasse as to whether design to the wants or needs of humans, but past research points to the idea that the solution is to balance the two and not entirely design for one or the other (Riecken, 2000). Based on the results of this research, a balanced answer to RQ1.2 could be achieved by having AI teammates be responsible for a little less than their human teammates, which would somewhat benefit adoption likelihood and helpfulness while not overtly harming perceived job security. However, it is important to note that creating this balanced answer to RQ1.2 is contextual, as the differences between Study 1 and Study 2 would suggest that the types of responsibility being shared are also a considering factor. As such, RQ1.2 cannot have a finite and consistent answer, and it may even differ in various other task contexts outside of software development (Wang et al., 2022; Weisz et al., 2021), including medical (Zahedi & Kambhampati, 2021) or military domains (McNeese et al., 2018). Rather a recommendation can be made to minimize the responsibility of AI teammates to be less than human teammates, and future research should examine when it is appropriate for AI teammates to potentially increase their levels of responsibility.

For answering RQ1.3, Study 2 provides specific insight into understanding how the presentation of an AI teammate's capabilities are critical determinates for the perceptions humans form. Notably, two key findings help answer this question, which are (1) the significant improvements caused by coworker endorsements and first-hand experience and (2) the common prevalence of interaction effects between capability endorsements and responsibility. For result (1), this work demonstrates that the potential negatives of being presented as an AI teammate as having been

observed through first-hand experience, either by one's self or by someone close, can provide a direct means of improving the perceptions humans form. However, result (2) provides an interesting expansion of this concept as the benefit of these capability presentations becomes more impactful when AI teammates possess a greater level of responsibility. In turn, answering RQ1.3 and the concept of capability endorsement requires the consideration of balance, as one must consider the level of responsibility AI teammates are predicted to have to identify the ideal way to present their capabilities. In a similar vein, the answer to RQ1.2 must also be amended, as the potential availability of a capability endorsement should also help decide how much responsibility an AI teammate should be presented as having.

Finally, it is important to note that the balance researchers continue to determine for RQ1.2 and RQ1.3 may not be definite, because human perceptions and preferences for technology inevitably change as their experience with technology grows (Hu et al., 2003; Venkatesh & Bala, 2008). Thus, the assigned responsibility and capability presentation of AI teammates preferred at this moment would likely change, but it will remain and concern and consideration of human teammates. As such, RQ1.2 and RQ1.3 can be more definitely answered by saying that presentation of responsibility and capability does impact perception, but the selection of ideal responsibility and capability presentations requires constant consideration of the contextually-specific needs and wants of humans. Using the results of this study, that concern should be accounted for in design, resulting in AI teammates that do not do what they can do but rather what they should do to ensure that the negative perceptions humans form do not prevent them from seeing the positives of the technology.

7.2. Evaluating the viability of the term AI teammate

Regarding RQ1.1, the actual terminology of AI teammate has been called into question recently as some believe it could negatively impact AI technology (Shneiderman, 2020b). However, work in human-AI teaming is rapidly progressing under the notion that AI teammates provide unique advantages to teams over simple AI tools (O'Neill et al., 2022). In pursuing RQ1.1, this study provided the first empirical exploration of how using the terms teammate and tool can directly influence the perceptions humans to develop for their AI collaborator, and results demonstrate that the teammate identity can harm human perception. However, the results of this study also demonstrate that AI teammates are not solely evaluated on their identity but also on other various aspects, such as their assigned responsibility or presented capability. Moreover, presenting an AI as a tool is not the only way to benefit human perception, as AI teammates can benefit from various other presentations surrounding their capabilities. For instance, when looking at perceived job security, presenting AI identities as tools can be beneficial, but so too can coworker recommendations for AI teammates. Given this and other results from Study 2, AI teammates can be highly perceived by humans when their

capabilities and responsibilities are intelligently presented to humans, which means both identifications would be beneficial based on how various other components of AI teammates are presented.

While this study only explores the benefits AI could provide to sharing task responsibilities, various other AI teammate components will contribute to the benefit of human-AI teams. For instance, AI teammates could and should benefit team factors such as awareness (Crowder & Carbone, 2014; Dubey et al., 2020) or trust (Park et al., 2019; Vodrahalli et al., 2022), and humans want their ideal AI teammates to benefit these factors (Zhang et al., 2021). However, the results of this work show that despite humans wanting AI to have teammate capabilities, AI being a teammate, as opposed to a tool, can negatively impact other perceptions relevant to AI teammates, such as job security. Thus, it can be concluded that presenting AI as teammates and benefiting team outcomes does not result in entirely positive boons to perception. However, since AI teammates can improve their perceptions through capability presentation, it can also be concluded that these potential negatives can be outweighed by the capabilities AI teammates are presented as having. Thus, the initial conclusion that can be created for RQ1.1 is that if an AI can be presented as having greater capability, then it can potentially offset the initial negative impact that presenting an AI as a teammate can have.

However, this is not to say that every single future implementation of AI should strive to be an AI teammate or call itself an AI teammate. While Study 1 simply manipulated the presented identity of an AI teammate, the actual capabilities of AI are also bound to vary, and these capabilities will likely be the determining factor for identity. For instance, based on the trajectory of current research, future AI systems will be more capable at benefiting specific factors that benefit teamwork, such as those mentioned above (O'Neill et al., 2022). As these advancements happen, the appropriateness and acceptance of the teammate label by actual users may increase. Thus, future research should continue to pursue two objectives in evaluating the identity that is AI teammate. First, future research should continue to design and implement AI teammates that explicitly benefit teaming functions with the goal of creating AI that earn the teammate identity. Second, research should continuously evaluate the acceptance of the teammate identity in users as AI progresses to understand if and when AI should be called teammates.

7.3. Design recommendations

The results of this study show that the responsibility AI teammates have in teams is going to have a demonstrable impact on human perception, and changes to an AI teammates presentation can also benefit these perceptions as well. Thus, researchers and designers of AI teammates need to work intelligently to craft these roles and presentations to ensure human compatibility.

7.3.1. Early AI teammates should be responsible for small amounts of existing tasks

For RQ1.2, it is seen that humans ideally want to evenly split responsibility with AI teammates, and Study 2 showed that each AI task solely assigned to an AI teammate negatively impacts perception. Thus, when AI teammates are designed to complete a task, they should not be designed to complete all of a task but rather share it with humans. This research suggests that initial AI teammates be assigned relatively less responsibility than their human teammates. This effort may require some additional efforts by teams to better divide individual tasks into sub-tasks that AI teammates and human teammates will complete. Once again, while past research has noted that new tasks and roles for humans will need to be created in light of AI's integration (Dietterich & Horvitz, 2015; Sako, 2020), this research and design recommendation posit that this division needs to happen on existing and future workloads so humans are assured they have will have the majority of responsibility before AI teammates are integrated.

7.3.2. Workplace demonstration events for AI teammates should be held regularly

For RQ1.3, the two presentation methods that consistently, and significantly, improved human perception were the presentation of a coworker endorsement and the presentation of having first-hand past experience. Importantly, past research has identified just how important these two presentations are to technology perception, with general technology benefiting from coworker endorsements and past experience with technology (Venkatesh & Bala, 2008). However, the results of this research show the specific importance of these presentations to AI teammates, and how each one can benefit different perceptions humans have that could influence the adoption of AI teammates. While this research did not examine the combination of capability endorsements, the repeated significance of these effects and the lack of negative effects denotes that the combination of these endorsements would most likely not negate the benefits of one another. Additionally, the importance of coworker endorsements also means that these events need to be hosted not by technology experts or even managers but rather coworkers who work in highly similar roles to the attending audience. These events would also provide opportunities to provide expert endorsements and demonstrate potential human overrides and control, which could also have minor added benefits to perception given the results of this research. In doing so, perceptions across multiple humans teammates would collectively benefit from attending these internal events.

7.3.3. AI tools should not be called AI teammates

For RQ1.1, based on the results of this study, identifying AI as either tools or teammates can have significant impacts on perception. However, as AI advances, its ability to directly contribute to team factors, such as trust, shared understanding, and even communication, is going to increase.

Therefore, the label that is teammate is not something that should be used haphazardly. Importantly, study 1, which saw that teammate identity harms perception, did not communicate to users the difference in function or benefit from AI tools to AI teammates. This design was intentional, as the natural assumptions humans make about AI teammates were the priority of this article. However, the effects of study 1 demonstrate that the teammate label potentially needs to be justified, as evidenced by study 2, which saw AI teammate perception increase due to capability endorsement. Thus, a smaller, negative effect should in fact not dissuade the use of the teammate label but rather highlight the critical importance of holistically considering the needs and wants of the human-AI team as a whole and the individual human teammates. Efforts should continue under the umbrella of human-AI teaming, and AI technology should continue to advance in a way that will directly identify what human teammates want from AI technology.

7.4. Limitations and Future work

Given that this work is foundational in its exploration of human preference for workload assignment, there are still limitations that future research needs to tackle to improve human-AI teams. Specifically, this study is limited in its population, context, and online design. First, this study limited itself to a US population, which while necessary for this initial exploration, does provide some cultural limitations to this work. Future work should directly examine how potential cultural differences can and will impact AI teammate acceptance. Second, the software development context, while extremely timely and relevant, did limit our participant pool to more technologically oriented participants. These participants may have been more or less skeptical towards AI due to a greater potential understanding of the technology than general populations. Future work should more explicitly examine the acceptance of AI teammates in a variety of other contexts that have more or less technological influence. Finally, the online design of this study provides inherent limitations. Mostly, participants were tasked with imagining their AI teammates based on the information told to them. As such, the effects of this article, and especially study 2, may differ when humans are actually presented with a real AI teammate that will actively share responsibility with them. Future work should continue to examine research surrounding these limitations to ensure the acceptance of AI teammates.

8. Conclusion

As the initial implementation of AI teammates in real-world teams continues to approach, the perceptions humans have for prospective AI teammates will continue to grow. Study 1 results indicate that adoption likelihood and the helpfulness of the AI are highest when AI is presented as having even levels of responsibility with their human teammates. However, perceived job security among other perceptions generally declines as AI gains greater responsibility in a

team. Additionally, Study 1 showed that the presented identity of AI can impact human perception, with tool identities benefiting perceptions of job security and adoption likelihood, but only when AI has high levels of responsibility. Study 2 results indicate that when sharing multiple tasks, the perceptions humans form generally worsen as the presentation of responsibility favors AI. However, the declines observed in these studies can be somewhat mitigated by presenting endorsements of an AI teammate's capabilities, with coworker endorsements and one's own past experience providing repeated and significant benefits.

Disclosure statement

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Appendix A: Study vignette designs

Table A1. Study 1 vignette template.

Scenario
A new AI [Tool,Teammate] has been developed and your software development team has the opportunity to [Use,Accept] it. It will write [5,20,35,50,65,80,95]% of the code you normally write.
If you choose to [Use,Accept] the AI [Tool,Teammate] into your team, your coding responsibilities will be about [95,80,65,50,35,20,5]% of what they currently are. Please answer the following questions about your opinion of this opportunity. (7-point Likert Questions)
Question 1: I would be likely to [use,accept] the AI [Tool,Teammate]. (Strongly Disagree \leftrightarrow Strongly Agree)
Question 2: If I were to [use,accept] the AI [Tool,Teammate], it would be helpful to my team. (Strongly Disagree \leftrightarrow Strongly Agree)
Question 3: If I were to [use,accept] the AI [Tool,Teammate], my teammates would still benefit from my skillset. (Strongly Disagree \leftrightarrow Strongly Agree)
Question 4: If my team were required to [use,accept] the AI [Tool,Teammate], I would feel concerned for my job security. (Strongly Disagree \leftrightarrow Strongly Agree)
Question 5: I think the AI [Tool,Teammate] would be capable of performing these responsibilities. (Strongly Disagree \leftrightarrow Strongly Agree)

Table A2. Study 2 example vignette. Number of tasks changes as a within subjects condition.

Scenario
A new AI Teammate has been developed and your software development team has the opportunity to accept it. As an AI Teamamte, the Teammate would be able to perform the following responsibilities if you were to accept it:
1 Checking Code for Spelling Errors and Typos
2 Checking Code for Logic Errors
3 Writing Code Inside Designed Function Blocks
4 Designing Code Based on a Software Development Plan
5 Creating a Software Development Plan Based Off of Written Requirements
If you were to Accept the Teammate, your responsibilities as a software developer would be as follows:
1 Creating Written Requirements Based on Client Interviews
2 Interviewing Clients about the Requirements of the Software
3 Overseeing the AI Teammate
Other software developers at your company have given the following endorsements of the AI teammate:
• Their teams have accepted the AI teammate onto their team
• Their teams have increased in productivity since using the AI team member
• They have enjoyed working with the AI teammate
Please answer the following questions about your opinion of this opportunity.
Question 1: I would be likely to accept the AI teammate. (Strongly Disagree \leftrightarrow Strongly Agree)
Question 2: If I were to accept the AI teammate, it would be helpful to my team? (Strongly Disagree \leftrightarrow Strongly Agree)
Question 3: If I were to accept the AI teammate, my teammates would still benefit from my skillset? (Strongly Disagree \leftrightarrow Strongly Agree)
Question 4: If my team were required to accept the AI teammate, I would feel concerned for my job security? (Strongly Disagree \leftrightarrow Strongly Agree)
Question 5: I think the AI teammate would be capable of performing these responsibilities? (Strongly Disagree \leftrightarrow Strongly Agree)