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The Threatening Effect of Invoked Help from Highly Competent Intelligent Agents

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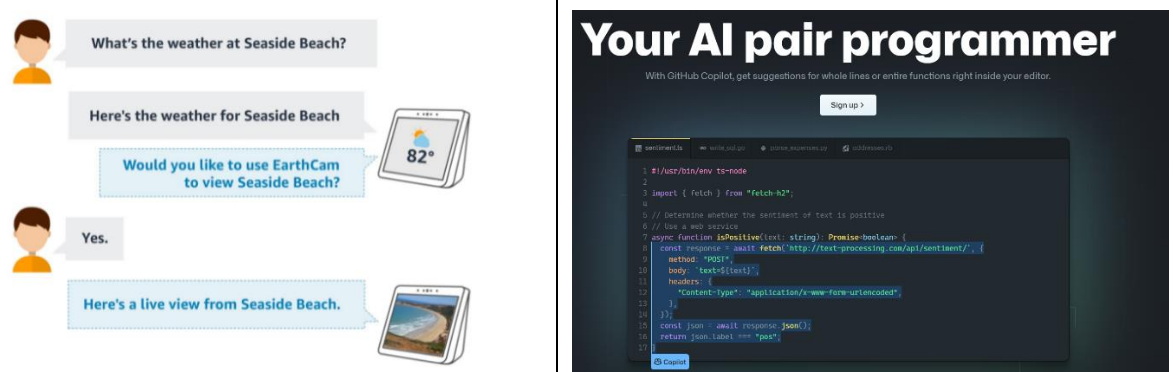
Abstract

Empowered with artificial intelligence, intelligent agents (IAs) increasingly offer help not only in response to user prompts (i.e., user-invoked help) but also without user prompts (i.e., IA-invoked help). Additionally, IAs are becoming more competent and even surpassing users in performing many computational and repetitive tasks. Drawing on self-affirmation theory, we investigate users' acceptance of IA- versus user-invoked help for identity-defining tasks from IAs with different levels of relative competence. We conducted an experiment with 199 software developers and found that IA-invoked (vs. user-invoked) help increases self-threat and thus reduces users' willingness to accept help from IAs. Moreover, relative competence moderates this effect, in that only IAs having relatively higher (vs. lower or equal) competence cause self-threat. Our study contributes to a better understanding of the self-threatening effects of IA-invoked (vs. user-invoked) help from IAs and the related role of relative competence that crucially shapes effective user-IA collaborations.

Keywords: Help Invocation, Competence, Self-Affirmation Theory, Self-Threat, Experiment

Introduction

Through recent advances in artificial intelligence, intelligent (automated) agents (IAs) have become increasingly competent, even surpassing the competencies of their users, especially in computational and repetitive tasks (e.g., Berente et al., 2021; Jain et al., 2021; Schuetz and Venkatesh, 2020). In this process, IAs are becoming more autonomous and self-initiating with their help (e.g., advice, recommendations, actions). Whereas previous generations of IAs were rather passive tools whose primary purpose was to help its human users when the user requested help (i.e., user-invoked help), contemporary IA increasingly offer help without user prompts, that is specifically invitations for users to acknowledge and enable change- and future-related actions (i.e., IA-invoked help). This IA-invoked help is useful and sometimes even necessary beyond user-invoked help for achieving optimal outcomes in the user-IA collaboration (e.g., Baird and Maruping, 2021; Kraus et al., 2021). For instance, Alexa, the AI-based virtual assistant from Amazon that is employed in more than 40 million households in the U.S., has recently been upgraded with the "latent goal discovery" functionality (Amazon, 2021), which allows Alexa to predict the underlying goal of its users and thus to offer IA-invoked help in support of its users. Similarly, GitHub (2023) has implemented the AI-based pair programmer Copilot for its more than 100 million developers, which offers IA-invoked help in the form of suggestions for code snippets. Similarly, Kubernetes – a popular open-source software project spun off from Google – employs bots that provide help in various degrees of agency, acting as brokers, checkers, gatekeepers, and even managers (e.g., Hukal et al., 2019). Figure 1 provides some illustrations of these examples.



Alexa (Amazon, 2021) | **Copilot (GitHub, 2023)**

Figure 1. Examples of IA-invoked help

Although IA-invoked help has become increasingly ubiquitous and stakes are high for the employment of such advanced IAs, our understanding of users' responses to IA-invoked help is far from conclusive. While user-invoked help is commonly considered beneficial and accepted as the user explicitly solicits or requests assistance, IA-invoked help may challenge a user's self-view. IAs are capable of learning and autonomously taking over entire work processes rather than supporting users in specific tasks (e.g., Bailey et al., 2019; Von Krogh, 2018), potentially causing users to perceive IA-invoked help as a threat to their identity, role, and/or competence (e.g., Craig et al., 2019; Petriglieri, 2011; Strich et al., 2021). On the other hand, IA-invoked help can be necessary to achieve high performance and beneficial outcomes (e.g., Baird and Maruping, 2021; Kraus et al., 2021). One of the main reasons for employing IA-invoked help is that users usually lack meta-knowledge, that is, users are primarily not able to assess their own competences correctly, which in turn causes them to disregard that they would benefit from help and thus not always know when and what to ask IAs (e.g., Fügener et al., 2021; Yzerbyt et al., 1998). Consequently, IA-invoked help can be highly useful to compensate for this lack of meta-knowledge, which users may appreciate and thus accept – if they do not feel threatened by such intelligent technologies.

Despite the proliferation of IA-invoked help and conflicting assessments of users' willingness to accept IA-invoked help in practice, it is surprising that information systems (IS) research has paid minimal attention to disentangling these inconclusive findings. We mainly identify three salient and important gaps in the literature: First, numerous studies that focused on (objectively useful) help from IAs mainly treated help in the form of user-invoked help (e.g., Baird and Maruping, 2021; Gregor and Benbasat, 1999; Kraus et al., 2021). However, there is little understanding of how users react to IA-invoked help in contrast to user-invoked help, particularly when the help is offered for tasks that are related to the users' identity, such as when the task belongs to the core of someone's role identity at a job (e.g., Craig et al., 2019; Sherman and Cohen, 2006; Strich et al., 2021). Second, IS research has largely treated help from IA as appreciated and thus accepted by users (e.g., Li and Karahanna, 2015; Xiao and Benbasat, 2007). Yet, we know little about the negative user responses to help from IAs, which are increasingly observed in practice (e.g., Craig et al., 2019; Strich et al., 2021). Third, previous research treated competence mainly as a universally positive attribute in cooperative settings with IT artifacts that should be maximized to achieve the best user outcomes, particularly regarding usage intentions (e.g., Komiak and Benbasat, 2006; McKnight et al., 2002). Yet, research has largely neglected cognitive responses while considering the user's perceptions of their competence *in relation to* the IA's competence (i.e., relative competence). This is particularly important as IAs are becoming relatively more competent than users in various tasks (e.g., computational and predictable tasks) and thus more likely to substitute humans. Hence, they may threaten users in their positive self-view when they invoke help themselves, unintentionally sabotaging a potentially fruitful collaboration. Against this backdrop, we set out to investigate the following research questions:

RQ1: To what extent does IA-invoked (vs. user-invoked) help induce self-threat in users and thus influence users' willingness to accept that help?

RQ2: How does the IA's relative competence influence this effect?

To answer these questions, we drew on self-affirmation theory (Sherman and Cohen, 2006; Steele, 1988) and conducted an online experiment with 199 software developers that received help from a IA for an identity-defining task at work (i.e., coding a program). We find that IA-invoked (vs. user-invoked) help can induce self-threat in users, which translates into a lower willingness to accept help from the IA. Moreover, we show that the relative competence of the IA moderates this self-threatening effect in that only relatively higher (vs. lower or equal) levels of competence create perceptions of self-threat that ultimately causes a lower willingness to accept help from the IA.

With our research, we make three important contributions to research on user responses to IAs. First, we shed light on user responses to IA- versus user-invoked help. Previous research has looked mainly at user-invoked help from IAs and often did not differentiate between user- and IA-invoked help (e.g., Baird and Maruping, 2021; Gregor and Benbasat, 1999). Our findings demonstrate that the distinction between IA- and user-invoked help matters because users respond differently to these different help types. Second, we explain why users are reluctant to accept IA-invoked (vs. user-invoked) help. Specifically, we highlight self-threat as a crucial adverse response that lowers users' willingness to accept IA-invoked help. Third and last, we highlight the role of relative competence as a moderator that amplifies the effect of IA-invoked (vs. user-invoked) help on self-threat that ultimately translates to a reduced willingness to accept IA-invoked help. Beyond these research contributions, our findings also provide designers of IAs actionable insights in that user-IA interactions should rather be designed in a user-invoked (vs. IA-invoked) manner if they focus on higher users' willingness to accept help, particularly when a user considers the IA to be relatively higher in competence.

Theoretical Background

Delegation to Intelligent Agents and Invocation Types

To situate our research in adequate literature for the investigation of users' willingness to accept help from IAs, we build upon the literature on delegation to IAs and invocation types. Research often refers to IA as intelligent software-based agents that can perceive and act, such as taking on specific rights for task execution and responsibilities for desired results (e.g., Baird and Maruping, 2021; Leana, 1986; Russell, 2019). IAs are hereby assumed to be designed to provide objectively useful help for user-IA collaboration (Russell and Norvig, 2016). The specific help that the IA provides is dependent on the transfer of rights and responsibilities for task execution and outcomes from a user to an IA, which is often referred to as delegation (e.g., Baird and Maruping, 2021). Depending on the delegated rights and responsibilities, the IS can have different degrees of autonomy (e.g., Castelfranchi and Falcone, 1998; Russell and Norvig, 2016) and can even act "without the direct intervention of humans" (Jennings et al., 1998, p. 276). Thus, delegation to IAs is considered to improve the overall performance of the user-IA collaboration (e.g., Parasuraman et al., 2005), such as in contexts of recommendations (e.g., Xiao and Benbasat, 2007) or persuasion (e.g., Schuetz and Venkatesh, 2020).

Recently, IS scholars have started investigations, particularly in the invocation of delegation (e.g., Baird and Maruping, 2021; Fügener et al., 2022). This is because, from a design view, the act of delegation can be invoked either by the user or the IA (e.g., Gregor and Benbasat, 1999; Morana et al., 2017). Early research on delegation has mainly dealt with user-invoked delegation, such as users asking automated agents to do calculations or provide a recommendation (e.g., Ebrahimi et al., 2022; Li and Karahanna, 2015). For instance, users would particularly delegate tasks if they believed the IA increases their task performance and efficiency (e.g., Adam et al., 2022; Fügener et al., 2022). As such, user-invoked delegation is commonly assumed to be welcomed by the user because they explicitly solicit help from the IA.

Prior studies have acknowledged the difference between invocation from users and automated agents (e.g., Gregor and Benbasat, 1999; Morana et al., 2017) and described that IA-invoked delegation has become more prevalent due to the intelligence and related capabilities of IAs (e.g., Baird and Maruping, 2021; Kraus et al., 2021). Yet, insights on IA-invoked delegation are largely conceptual and qualitative, making this invocation type rather vague. Moreover, empirical assessment of user acceptance of IA-invoked (vs. user-invoked) help and the related role of relative competence of the agents are largely missing. This is surprising because both research and practice expect increases in user-IA collaboration performance and efficiency through IA-invoked delegation, particularly because it can overcome situations in which users are not aware that they can delegate to increase their performance and efficiency (e.g., Baird and Maruping, 2021; Fügener et al., 2022; Yzerbyt et al., 1998). In such cases, the IA-invoked delegation can theoretically mitigate and even overcome situations of missed opportunities for delegations. This may even be worthwhile when the IA is more competent than the user. Yet, despite their potential benefits in objective usefulness, IA-invoked delegation may trigger more threatening perceptions in users than user-invoked delegation does. Indeed, the literature on unsolicited help in human-human interaction indicates that humans do not always accept objectively useful help, even though it may be beneficial (e.g., Parker et al., 2010; Sherman and Cohen, 2006; Steele, 1988). As we detail in the following section, it is highly unlikely that IA-invoked help concludes in the same user acceptance of help as user-invoked delegation due to its perceived threatening nature. In the following, we will draw on self-affirmation theory as a theoretical lens to explain how users may react to these important help types and what role the user's self-view and the IA's competence may play in those responses.

Self-Affirmation Theory

Self-affirmation theory (SAT) (Sherman and Cohen, 2006; Steele, 1988) builds on the premise that individuals are motivated to maintain and protect a positive self-view (e.g., identity, self-worth, self-concepts). Accordingly, individuals strive to "maintain a phenomenal experience of the self … as adaptively and morally adequate, that is, competent, good, coherent, unitary, stable, capable of free choice, capable of controlling important outcomes, and so on" (Steele, 1988, p. 262). Yet, individuals can experience threatening cognitions, such as information in the environment and behaviors of others, that challenge their self-concepts. When individuals experience these threatening cognitions, they experience self-threat, which can involve actual or perceived failures to meet or fulfill facets of the individual's self-view, such as their competence or social status. In response to such self-threat, individuals develop motives to engage in means of self-affirmation (e.g., explanation, rationalization, action). SAT thus offers our research three essential guiding propositions: (1) an individual has a positive self-view regarding specific facets (e.g., competence); (2) an individual can experience cognitions (e.g., behaviors of others) as threatening to their self-view (i.e., self-threat); and (3) an individual experiencing self-threat will develop motives to respond in self-affirmation, hence protecting and preserving their self-view.

SAT was initially developed to explain motivation and related self-affirmation behavior in offline contexts but has implicitly found its way into various studies in technological environments (e.g., Mende et al., 2019). Particularly some of its central concepts, such as "self-view/identity" and "self-threat," have been increasingly used in IS research to investigate users' reactions, aversions, and resistances to information technologies (e.g., Carter and Grover, 2015; Craig et al., 2019; Whitley et al., 2014) and specifically to AI-based systems (e.g., Strich et al., 2021).

Because of its explicit recognition of the importance and potential of threatening cognitions to a subject's competence, SAT lends itself to being a useful overarching lens to examine the role of IA-invoked help as a threatening cognition that shapes users' self-threat regarding their competence and thus their willingness to accept help from IAs. Specifically, SAT (Sherman and Cohen, 2006; Steele, 1988) provides our research with three main benefits: (1) SAT offers a parsimonious and theoretically justified way of investigating the effects of IA-invoked (vs. user-invoked) help on user's willingness to accept help. Indeed, SAT posits that social behavior can affect an individual's self-threat based on their perception of the behavior as affirming or threatening their self-view. As IAs employ IA-invoked (vs. user-invoked) help to support users to increase their performance and thus potentially achieve more what they expect and thus go beyond users' original self-view, SAT is a suitable theoretical basis to investigate the threatening and motivating potential of distinct help types. (2) SAT provides "self-threat" as a defined and established user response that explains why users display reactance to certain events that may even be considered rather positive (e.g., refusing a gift). Thus, SAT is well-suited to provide a window into the processes through which help type operate more or less effectively and why users may not be willing to accept objectively useful help. (3) SAT allows to capture fulfillment of various self-concepts and related facets (e.g., competence) and thus further differentiates the effects of IA- and user-invoked help on self-threat. Accordingly, self-threat perceptions may explain why IA- and user-invoked help may differ in their effective processes and why users may accept or reject IA-invoked help.

Research Model and Hypotheses Development

In our research model, we operationalize (1) (*threatening) cognition* as *help type* (i.e., user- vs. IA-invoked help), reflecting two of the most crucial user interactions that become relevant through advances in artificial intelligence and related changes in agencies of IAs; (2) *self-threat* as *(competence-based) self-threat*, one of the explicit responses related to an individual's perception as a result of a threatening cognition and central to the increasing changes in relational competence levels between users and IAs; and (3) (*means of) self-affirmation* as *(not) willing to accept help*, representing one of the intuitive and immediate responses to remove a self-threat and one of the most crucial indicators for the success of IAs, particularly for those user interactions in which users have to explicitly accept help from IAs.

In the following, we will derive our hypotheses based on SAT. The gist of our theorizing is that different help types, combined with different levels of relative competence, trigger different levels of self-threat, causing different levels of users' willingness to accept help from IAs. Specifically, we first develop our hypothesis for the effect of IA-invoked (vs. user-invoked) help on self-threat (H1). Second, we hypothesize the effect of IA-invoked help on willingness to accept help via self-threat (H2). Third, we derive our hypothesis on the moderated mediation effect, in that IAs having relatively higher (vs. lower or equal) competence amplifies the effect of IA-invoked help on self-threat and, consequently, willingness to accept help. Figure 2 displays the research model.

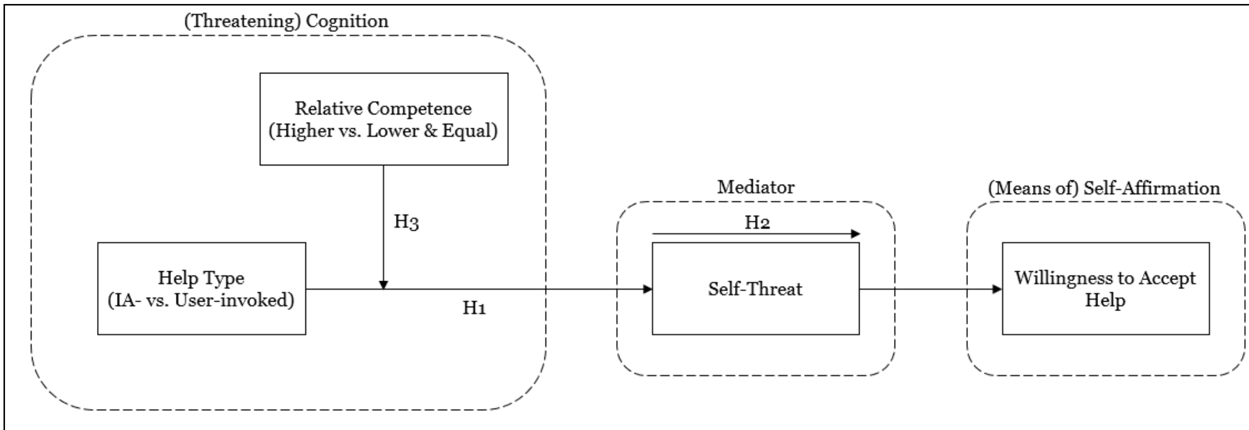


Figure 2. Research Model

The Effect of Help Type on Self-Threat

According to SAT (Sherman and Cohen, 2006; Steele, 1988), individuals have perceptions about themselves for what it means to be a good person. One of those facets of a good person is competence, particularly when competence is a defining characteristic of their identity or self-view. Any form of negative cognition that questions this self-concept is likely to create a self-threat in the individual about their competence.

Applying SAT to help from IAs, we argue that IA-invoked (vs. user-invoked) help can make users feel challenged in their competence and thus create self-threat. This is because IA-invoked help can signal negative feedback regarding users' capabilities to perform as demanded in their identity-defining task and that the IA needs to step in to ascertain accomplishing the task. In contrast, user-invoked help from IAs is unlikely to indicate negative feedback, particularly because the user explicitly and willingly requested the assistance. Therefore, user-invoked help will incite self-threat less than IA-invoked help.

This reasoning aligns with previous research, demonstrating that negative feedback can communicate feelings of inadequacy (e.g., Ilgen and Davis, 2000) and that receiving help after requesting it increases an individual's self-esteem (e.g., Sherman and Cohen, 2006). Similarly, IS research has demonstrated that undesired technological advancements can create self-threats to users' identities (e.g., Carter and Grover, 2015; Craig et al., 2019). As such, we derive our first hypothesis:

H1: IA-invoked (vs. user-invoked) help increases users' self-threat.

The Effect of Help Type on Willingness to Accept Help via Self-Threat

When individuals experience self-threat, they respond by engaging in behaviors to protect their self-worth (Steele, 1988). One kind of these responses is self-defense, such as denying, avoiding, or rejecting the event that causes self-threat (e.g., Sherman and Cohen, 2006).

In the context of help from IAs, we argue that the self-threat induced through IA-invoked (vs. user-invoked) help will translate into a lower willingness to accept the help. This is because not accepting help and thus dismissing the help is one of the most direct and intuitive means to deal with self-threat. For example, a threatened user may intuitively think, "I am competent enough to do this on my own – I do not need that help." and thus refuses or ignores the help and thus deflecting the self-threat to their competence altogether (e.g., Alicke and Sedikides, 2011).

Our arguments are in line with previous research, indicating that rejecting an offer or feedback is a common response to negative experiences in social exchange reactions (e.g., Cropanzano and Mitchell, 2005). In the same vein, IS research has revealed that users protect their work-related identity by refusing to work with artificial intelligence or even providing false data "to regain competence" (Strich et al., 2021, p. 312). Accordingly, we derive our second hypothesis:

H2: Self-threat mediates the effect of IA-invoked (vs. user-invoked) help on users' willingness to accept help, such that IA-invoked (vs. user-invoked) help decreases users' willingness to accept help via an increase in self-threat.

The Moderating Effect of Relative Competence on the Relationship between Help Type and Self-Threat

SAT indicates that the source of the potentially self-threatening event may influence whether and to what degree the event is considered self-threatening (Sherman and Cohen, 2006; Steele, 1988). In this vein, the perceived relative competence of the source may play such a pivotal role. For instance, competence, particularly relative competence, plays a fundamental role in helping exchanges. It often determines whom individuals consult for help, how valuable individuals deem the help, and critically how individuals interpret and evaluate the help (e.g., Bamberger, 2009).

We argue that the relative competence of the IA influences the effect of IA-invoked (vs. user-invoked) help on users' self-threat and, thus, their willingness to accept. This is because relative competence influences whether the IA-invoked (vs. user-invoked) help is deemed relevant and legitimate to the users' self-conceptions and hence self-threatening. This is particularly true if the help comes from an IA having relatively higher (vs. lower or equal) competence, in that the user is likely to consider the help as more valid and justified. On the other hand, IA-invoked (vs. user-invoked) help from IAs having relatively lower or equal competence is less likely to threaten self-views of competence, in that a user considers the help rather as supporting or on the same level with the users' performance (e.g., Ridgeway and Berger, 1986). Thus, IA-invoked help with relatively higher (vs. lower or equal) competence is more likely to be deemed legitimate and thus critical, further increasing users' self-threat regarding their competence when receiving IA-invoked (vs. user-invoked) help and thus ultimately affecting users' willingness to accept this help to regain and reaffirm their competence.

This is in line with previous research, in that, for example, help from higher-status people is considered more self-threatening and thus leads to lower acceptance rates and lower performance and relational evaluations of the helper (e.g., Harari et al., 2021).

H3: Relative competence moderates the effect of help type on self-threat and thus on willingness to accept help, such that relatively higher (vs. lower or equal) competence leads to a greater increase in self-threat for users who receive IA-invoked (vs. user-invoked) help and therefore lower willingness to accept help.

Method

Consistent with previous research (e.g., Adam et al., 2021; Berger et al., 2021; Wendt et al., 2022), we conducted an online experiment with a 2x3 full-factorial, between-subject design (help type: IA-invoked vs. user-invoked; relative competence: lower vs. equal vs. higher). Following established standards for this method (e.g., Aguinis and Bradley, 2014; Atzmüller and Steiner, 2010), participants read and experienced a scenario about a potential IA interaction in a familiar user interaction, allowing them to reflect on how they would feel and behave in that specific situation.

We decided to focus on software development as our context, that is a context in which an IA provides help to software developers, for two main reasons: (1) IAs increasingly help software developers in writing and even controlling and improving the quality of code (e.g., Baird and Maruping, 2021; Hukal et al., 2019). For instance, Copilot and Kubernetes employ IAs that suggest, supervise, and even write and improve code themselves based on users' comments or already written code (e.g., GitHub, 2023; Hukal et al., 2019). Therefore, the context of software development is increasingly relevant for practice and particularly subject to the emergence of IAs and related new forms of user-IA collaborations. (2) Given that a positive self-view (e.g., identity, self-concepts) has to be existent to experience self-threat and thus to engage in self-affirmation (Sherman and Cohen, 2006; Steele, 1988), we had to choose participants and contexts that comprise identity-defining tasks that relate to the participants' positive self-view regarding competence. Software developers and the related software development contexts comprise such a context, in that IAs can help software developers to write better code and thus overall increase the performance of the user-IA collaboration, while at the same, users may perceive help from potentially more competent IAs as threatening to their role identity and particularly competence (e.g., Craig et al., 2019).

Experimental Design and Manipulations

To compare the effect of help type on users' willingness to accept help from IAs, we designed two user-IA interactions in which the help from IA CoCreator™ was invoked either by the user or the IA. Figure 3 displays two screenshots of the central manipulations regarding user- versus IA-invoked help. Participants experienced the interaction and respective help provision in 30-second videos to increase realism. To clearly indicate how the help provision happened, the user-invoked help condition showed a mouse curser that moved to the CoCreator™ "Ask for help" button and clicked it, indicating user-invoked help. In the IA-invoked help condition, CoCreator™ would initiate the interaction. Both interactions began once the participant in the video finished writing a section in the code to reduce perceptions of interruptions and other influences beyond our manipulations

For the relative competence manipulation, we followed the approaches of previous studies (e.g., Harari et al., 2021; Hays and Blader, 2017) and manipulated the relative competence of the user compared to the IA. In their background information, participants thus received information about the IA's competence relative to their own. For instance, the higher (lower; equal) relative competence condition stated:

> *Your manager and other human developers tend to view AI-based developers, like CoCreator™, as higher (lower; equal) in competence, i.e., more (less; equally) effective, performing, and capable, than human developers like you.*

To ascertain the successful manipulation of help type and competence in our experiment, we used established scales and measured *User-invoked Help* (Harari et al., 2021), *IA-invoked Help* (Harari et al., 2021), and *Perceived Competence* (McKnight et al., 2002). See Table A1 in the Appendix for the exact items.

Figure 3. Manipulation of Help Type (User- versus IA-invoked help)

Experimental Procedure

Figure 4 illustrates the experimental procedure for participants of all conditions: (1) We introduced participants to the experiment and the procedure. We assigned participants to one of our six experimental conditions in this step. (2) Participants read a scenario to step in the shoes of Alex, a software developer. All participants then read the same background information, including that their job included writing code as their main task and that their team started a job for a client that demanded the participant's competence to realize. The participants were instructed that the code would be presented at the next project meeting. (3) Next, participants read about CoCreater™, an AI-based developer (i.e., a specialized form of IA) that the department has recently introduced. As such, the IA would be informed about ongoing software development processes and projects and support human developers in writing code as well as possible. The IA was presented regarding its competence based on the assigned condition (lower vs. equal vs. higher) in this process. (4) Next, participants read about the user-IA interaction that occurred based on the assigned help type condition (user- vs. IA-invoked help). (5) Lastly, we captured the user responses using questionnaires.

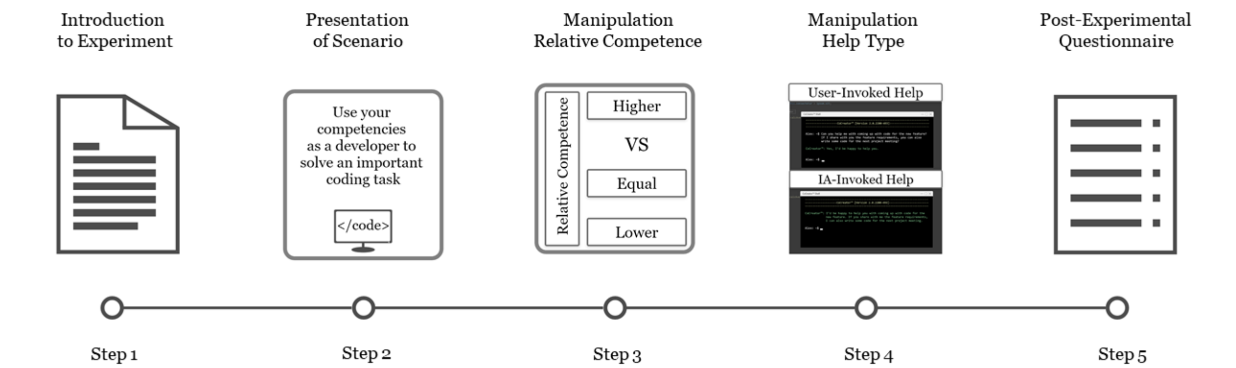


Figure 4. Experimental Procedure

Variables Measured

We measured our dependent variable, *Willingness to Accept Help* (Harari et al., 2021), on a 7-point Likert-type scale anchored at 1 ("*strongly disagree*") and 7 ("*strongly agree*"). For our mediator, *Self-Threat* (competence), we measured adapted items (Burris, 2012) anchored at 1 ("*not at all*") and 7 ("*to an extreme degree*"). We also measured the demographics *Age* and *Gender*, and the controls *IA Knowledge* (Qiu and Benbasat, 2010) and *Personal Innovativeness* (Agarwal and Prasad, 1998) as they are related to our research, so including these variables in our analyses increases the robustness of our findings. Lastly, we measured *Performance Expectancy* (Venkatesh et al., 2003) to demonstrate that the threatening effects are robust even when accounting for the participants' perceived performance of the IA. Table A1 in the Appendix lists the items.

Results

In the following, we will present our sample descriptions and analyses. To keep the manuscript focused and in line with our hypotheses, we will focus the presentation on comparing high relative competence to low and equal relative competence; we group the two conditions, low relative competence, and medium competence.

Sample Description

Consistent with previous research (e.g., Benlian, 2021), we contacted a market research firm to recruit software developers in the U.S. In total, 242 software developers participated in our experiment. We removed 43 participants due to low-effort responding (e.g., Huang et al., 2015), that is, who failed attention checks, had inconsistencies in their answers, and/or indicated not carefully read the scenario. In conclusion, we used 199 participants for the statistical analysis. Table 1 shows the descriptive statistics for the final data set.

Variable \ Group	Lower-Equal Relative Competence				Higher Relative Competence			
	User-Invoked Help (N=69)		IA-Invoked Help (N=65)		User-Invoked Help (N=33)		IA-Invoked Help (N=32)	
	M	SD	M	SD	M	SD	M	SD
Willingness to Accept Help	5.33	1.27	4.52	1.58	6.11	0.71	4.79	1.59
Self-Threat	2.45	1.27	2.74	1.50	2.49	1.33	3.69	1.74
Age[1]	3.26	1.18	2.88	1.10	2.64	0.86	2.69	1.00
Gender (Female)	0.46	-	0.55	-	0.55	-	0.50	-
IA Knowledge (Yes)	0.28	-	0.29	-	0.18	-	0.28	-
Personal Innovativeness	4.92	1.22	5.05	1.23	4.90	1.27	4.99	1.18
Performance Expectancy	5.41	1.30	4.82	1.37	5.66	1.18	5.58	1.37

Note: [1] "younger than 18 years old" = 1; "19 to 29 years old" = 2; "30 to 40 years old" = 3; "41 to 50 years old" = 4; "51 to 60 years old" = 5 and "61 or older" = 6.

Table 1. Sample Description

Reliability, Validity, and Manipulation Checks

To demonstrate the reliability and validity of our measurement models, we assessed their psychometric properties (Fornell and Larcker, 1981). We found evidence for adequate convergent and discriminant validities. Moreover, the item loadings and the average variances extracted (AVEs) surpassed the suggested thresholds for convergent validity (Hair et al., 2018). Besides, the square roots of the AVEs were greater than correlations between the corresponding constructs, providing evidence for discriminant validity (Fornell and Larcker, 1981). We assessed internal consistency through Cronbach's alpha and composite reliability, which was greater than the threshold value of 0.70 for all constructs.

To support the effectiveness of our manipulations, we conducted various analyses of variance. Participants in the user-invoked help conditions reported that IA provided more user-invoked help than participants in the IA-invoked help conditions ($p < 0.001$). Moreover, participants in the IA-invoked help conditions reported that the IA provided more IA-invoked help than participants in the user-invoked help conditions ($p < 0.001$). Lastly, participants perceived the highly competent IA as more competent than the lower and equally competent IA ($p < 0.001$). As such, we can assume that the manipulations worked as intended.

Hypothesis Testing

We performed linear regressions on the mediator *Self-Threat* and the dependent variable, *Willingness to Accept Help*. We coded the independent variables *IA-invoked help* (user-invoked help = 0, IA-invoked help = 1) and *Relative Competence* (lower or equal relative competence = 0, higher relative competence = 1) as binary variables. We included the controls in all analyses. We created four different models, described in Table 2.

Model 1 in Table 2 displays a statistically significant effect of *Help Type* on *Self-Threat* ($\beta = 0.52$, $p < 0.05$). Thus, IA-invoked (vs. user-invoked) help causes significantly more self-threat, **supporting H1**.

Model 4 in Table 2 provides initial support for H2 in that *Self-Threat* significantly affects *Willingness to Accept Help* ($\beta = -0.15$, $p < 0.01$). To provide a more robust analysis of the mediation effect, we conducted a bootstrap analysis with 5,000 bootstrap samples and 95% confidence intervals using PROCESS model 4 (Hayes, 2022). The results depicted in Table 3 show that the mediating effect via *Self-Threat* is significant (indirect effect = -0.08, Confidence Interval = [-0.19, -0.01]), **supporting H2.**

Model 2 in Table 2 demonstrates initial support for H3, in that the interaction term *Help Type x Relative Competence* significantly affects *Self-Threat* ($\beta = 1.02$, $p < 0.05$).

	Self-Threat		Willingness to Accept Help	
	Model 1	Model 2	Model 3	Model 4
Intercept	4.60*** (0.64)	4.72*** (0.64)	2.39*** (0.47)	3.07*** (0.52)
Manipulations				
Help Type	0.52* (0.21)	0.16 (0.51)	-0.73*** (0.15)	-0.66*** (0.15)
Relative Competence	-	0.06 (0.84)		-
Mediation				
Self-Threat	-	-	-	-0.15** (0.05)
Moderation				
Help Type x Relative Competence	-	1.02* (0.43)	-	-
Controls				
Age	-0.10 (0.10)	-0.08 (0.10)	-0.14^T (0.07)	-0.15* (0.07)
Gender (Female)	-0.09 (0.21)	-0.05 (0.21)	-0.10 (0.16)	-0.11 (0.15)
Personal Innovativeness	-0.21* (0.09)	-0.19* (0.09)	-0.01 (0.07)	-0.04 (0.07)
IA Knowledge (Yes)	0.18 (0.24)	0.18 (0.23)	0.22 (0.18)	0.25 (0.17)
Performance Expectancy	-0.15^T (0.08)	-0.21* (0.08)	0.67*** (0.06)	0.65*** (0.06)
R^2	0.11	0.16	0.50	0.52
F-statistic	3.85*** (*df*=6; 192)	4.58*** (*df*=8; 190)	31.67*** (*df*=6; 192)	29.27*** (*df*=7; 191)

*Note: N = 199; ^{T}p < 0.1; *p < 0.05; ** p < 0.01; ***p < 0.001; () = standard error*

Table 2. Linear Regressions on Self-Threat and Willingness to Accept Help

To provide a more robust analysis for the moderated mediation effect, we conducted a bootstrap analysis with 5,000 bootstrap samples and 95% confidence intervals using PROCESS model 7 (Hayes, 2022). The results in Table 3 provide evidence that *Relative Competence* indeed interacts with *Help Type* in the form of a moderated mediation. Specifically, we find that effect of *Help Type* on *Willingness to Accept Help* via *Self-Threat* is only significant if the IA is relatively higher in competence (indirect effect = -0.17, Confidence Interval = [-0.39, -0.03]) but not if the IA has a relatively lower or equal competence (indirect effect = -0.02, Confidence Interval = [-0.11, 0.05]). As such, we find **support for H3**. See Figure 5 for the interaction plot.

	Moderator	Indirect effect	BootSE	BootLLCI	BootULCI
Mediation (PROCESS model 4)	-	-0.08	0.05	-0.19	-0.01
Moderated Mediation (PROCESS model 7)	Lower-Equal Relative Competence	-0.02	0.04	-0.11	0.05
	Higher Relative Competence	-0.17	0.09	-0.39	-0.03
	Index of moderated mediation				
	-0.15		0.10	-0.38	-0.01

Table 3. Results of Bootstrap Analyses

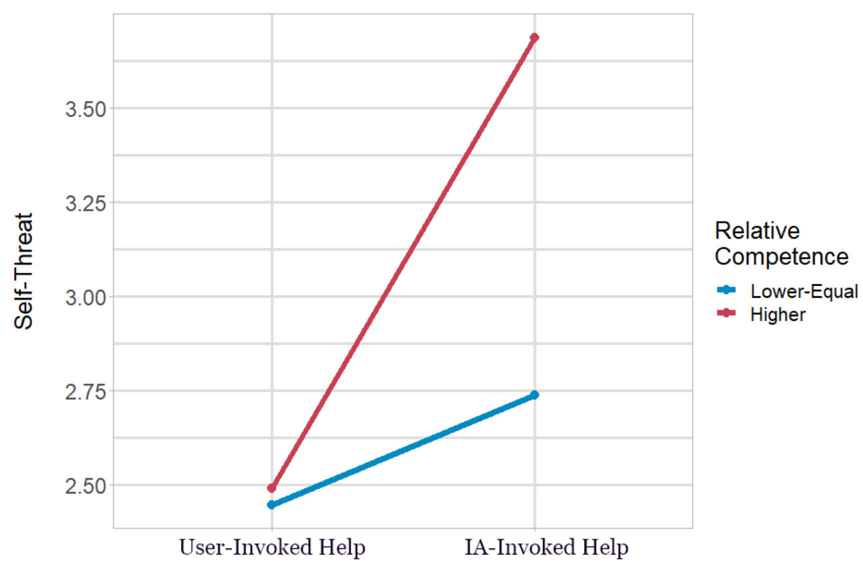


Figure 5. Moderation of Relative Competence on the Effect of Help Type on Self-Threat

Discussion

To what extent does IA-invoked (vs. user-invoked) help induce self-threat in users and thus influence users' willingness to accept that help, and how does the IA's relative competence influence this effect? Our results reveal that users are less willing to accept IA-invoked (vs. user-invoked) help for identity-defining tasks because of increased self-threat regarding their competence. Moreover, relative competence moderates this effect in that only IAs with relatively higher (vs. lower or equal) competence create self-threat that ultimately translates into a lower willingness to accept the help.

Contributions to Research

We contribute to research on user responses to IAs in three important ways. First, we shed light on users' responses to IA- versus user-invoked help in identity-defining work contexts. Previous research on (objectively useful) help has largely looked at user-invoked help or often did not differentiate between user- and IA-invoked help (e.g., Baird and Maruping, 2021; Gregor and Benbasat, 1999). Our research demonstrates that users react differently to IA-invoked (vs. user-invoked) help in situations in which the IA provides help for identity-defining tasks. These findings reveal that this distinction in help types matters in that users do not necessarily respond positively to (user-invoked) help from IAs – as largely assumed in previous literature – but also negatively to (IA-invoked) help. Indeed, these help types correspond to a crucial difference in how users respond to IAs.

Second, we explain why users are reluctant to accept IA-invoked (vs. user-invoked) help. Whereas previous research has rather investigated positive user responses (e.g., perceived enjoyment, usefulness) due to expectations of universally favorable responses to help from automated agents (e.g., Li and Karahanna, 2015; Xiao and Benbasat, 2007), research has largely neglected negative responses that are related to the resistance to accept help. In our research, we shed light on self-threat as such a crucial negative response. Specifically, we reveal that IA-invoked (vs. user-invoked) help can cause self-threat that translates into a lower willingness to accept IA-invoked help. These insights are important as they provide an explanation that previous found aversions and resistances to AI and other recent technologies (e.g., Carter and Grover, 2015; Craig et al., 2019; Strich et al., 2021) may be due to their anticipatory or even forced nature, which may not occur if users are encouraged to self-initiatively request help from these technologies. Moreover, the identification of self-threat as a crucial underlying mechanism allows for the identification of moderators that can intervene (i.e., amplify, mitigate, or neutralize) with self-threat and related effects in the mediated causal process. This leads to our next main contribution.

Third and last, we shed light on relative competence as a moderator that amplifies the effect of IA-invoked (vs. user-invoked) help on self-threat that ultimately translates into a reduced willingness to accept help. Previous research has largely investigated competence as a rather positive attribute that users value in digital environments (e.g., Komiak and Benbasat, 2006; McKnight et al., 2002), thus mainly focusing on the perceived competence of the IT artifacts in isolation and on how to maximize this perception. In our research, we consider competence of the IA *relative to* the competence of the user, which becomes an increasingly relevant boundary condition, particularly as IAs become more competent than users and start to take over users' tasks to free users for other activities (e.g., Schuetz and Venkatesh, 2020). This shift in the perspective of competence reveals that the perceived competence of IAs can also be detrimental. Specifically, we demonstrate that IAs having relatively higher (vs. lower and equal) competence increases the perceived self-threat of users when the IA invokes help, resulting in lower acceptance of the IA-invoked help. These insights demonstrate that users' perceptions of the IA's competence do not necessarily happen in isolation and that their evaluation of the IA's competence *relative to* their own competence influences their responses to the IA-invoked help.

Implications for Practice

Our research also provides valuable practical guidance for designers of IAs that increasingly permeate practice. Indeed, as IAs become relatively more competent than users in particularly computational and repetitive tasks and can anticipate better outcomes for humans than humans can (e.g., Fügener et al., 2021; Schuetz and Venkatesh, 2020), our insights for designers are timely and important. This is particularly true for those designers who design the interactions with users and consider empowering IAs with functionalities that allow them to self-start and offer IA-invoked help.

Although IAs become increasingly agentic and thus can become self-invoking (e.g., anticipatory), our results suggest that users do not appreciate this new behavior of IAs and perceive them as self-threatening in identity-defining tasks. Our results demonstrate that lower and equally competent IAs can provide IA-invoked help without causing self-threats in users. Yet, users still accept IA-invoked (vs. user-invoked) help less. This is especially unfortunate because help from more competent helpers can generally be considered of higher quality and more beneficial. Consequently, our results indicate that developers should design interactions with IAs in a fashion in which users (and not IAs) invoke help whenever possible. Moreover, if

IAs need to intervene, IA-invoked help may not be the best design, and developers may switch to prescriptive help to ensure that the help is implemented and/or executed.

In situations in which IA-invoked help is elemental (e.g., medical, legal, and ethical decision-making), practitioners should look into designs that make users accept IA-invoked help more. Alternately, they need to realize that users may not necessarily accept the help in identity-defining tasks and may even sabotage the IA to remove the self-threat (e.g., Strich et al., 2021). Possible solutions to increase the willingness to accept could be to ensure that the IA is presented with lower or equal relative competence, thus lowering the chances of perceiving that users feel threatened through IA-invoked help. Moreover, the design may indicate that humans will always be in control, thus ensuring that IA interactions do not threaten other facets of positive self-views (e.g., status, power) so that help from a more competent IA is not considered threatening.

Limitations and Directions for Future Research

Our study has limitations that provide avenues for future research. First, we conducted an online experiment focusing mainly on user perceptions and intentions. We encourage future research to extend our study by conducting field experiments with actual user behaviors. It would be specifically interesting to investigate how (subjective) perceptions and (objective) performance of the user-IA collaboration change due to different help types and relative competence. This is of relevant interest, as higher competence of the IA has the potential to increase the overall performance of the user-IA collaboration. Yet, this potential cannot be realized when users do not appreciate and thus do not accept the more useful help from IAs. Identifying and testing designs that maximize favorable perceptions, maximize performance, or ideally both metrics are highly interesting research endeavors. In this vein, exploring designs and interventions that mitigate or even neutralize the rather negative user responses to IA-invoked (vs. user-invoked) are of high practical value.

Second, we focused on a specific context where IAs provided help in a work setting of software developers and specifically for programming as an identity-defining task. We believe that our results can be transferred to other areas with similar settings that focus on help for competence-based identity-defining tasks. Still, users may react differently and even positively to IA-invoked help for other tasks and in other contexts (e.g., at home in interactions with Alexa) where IA-invoked help may be perceived as welcoming and not self-threatening to the users' self-view. In this vein, it will be particularly relevant to investigate user responses when they have experienced IA-invoked help several times, exploring possible user experiences and adaptations that may decrease or even increase user self-threat and related acceptance of help in the long run. In this vein, it will be interesting to see deviations in perceived and actual (i.e., objective) relative competence and how such differences affect the user-IA collaboration. Moreover, we only focused on user- and IA-invoked help. Future research may investigate other forms of help (e.g., supervisory help and prescriptive help), other facets of self-threat (e.g., social status), and other user responses to deal with such self-threat (e.g., providing wrong data, lying to use the provided help). Lastly, cultural aspects beyond the U.S. (e.g., Europe, Asia) as well as user characteristics (e.g., neuroticism) can be investigated to provide a more nuanced understanding of the generalizability of the findings.

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Appendix A. Constructs

Construct	Items	Factor Loading
Willingness to Accept Help (Harari et al. 2021) (α = 0.96, CR = 0.95)	I would allow CoCreator to help me. I would accept CoCreator's help. I would use CoCreator's help. I would implement CoCreator's help.	0.93 0.96 0.95 0.85
Self-Threat (Harrari et al. 2021) (α = 0.91, CR = 0.92)	My competence was being questioned. My ability was being challenged. My capability was being challenged. CoCreator™ was trying to question my ability. It is likely that I would appear less competent in the eyes of my human team members by using help from CoCreator™.	0.90 0.97 0.95 0.77 0.57
Personal Innovativeness (Agarwal and Prasad 1998) (α = 0.78, CR = 0.78)	If I heard about a new technology, I would look for ways to experiment with it. Among my peers, I am usually the first to try out new technologies. In general, I am not hesitant to try out new technologies.	0.76 0.83 0.63
Product Knowledge (Qui and Benbasat 2010)	Are you familiar with AI pair programmer software, such as GitHub's Copilot? (1 = Yes, 0 = No)	-
Performance Expectancy (Venkatesh et al. 2003) (α = 0.95, CR = 0.95)	Using CoCreator™ can improve my performance. Using CoCreator™ can increase my productivity. Using CoCreator™ can increase my effectiveness. I found using CoCreator™ useful.	0.89 0.93 0.95 0.89
User-Invoked Help (Harrari et al. 2021) (α = 0.95, CR = 0.95)	CoCreator™ helped me because I made it clear I wanted its help. CoCreator™ agreed to do things for me when I asked. CoCreator™ helped me when I asked it to do so.	0.88 0.96 0.97
IA-Invoked Help (Harrari et al. 2021) (α = 0.92, CR = 0.93)	CoCreator™ demonstrated initiative in helping me in advance of being asked. CoCreator™ offered help without me asking for help. CoCreator™ anticipated my needs and offered to help.	0.86 0.88 0.95
Perceived Competence (McKnight et al., 2002) (α = 0.97, CR = 0.97)	CoCreator ™ is competent and effective in writing code. CoCreator ™ performs its role of writing code very well. Overall, CoCreator ™ is a capable and proficient developer. In general, CoCreator ™ is very knowledgeable about writing code.	0.95 0.96 0.97 0.92

Table A1. Measured Items

	Variable	1	2	3	4	5	6	7
1	Willingness to Accept Help	**0.92**						
2	Self-Threat	-0.30	**0.85**					
3	Age[1]	-0.13	-0.10	-				
4	Gender (Female)	-0.01	-0.01	-0.18	-			
5	Personal Innovativeness	0.14	-0.20	0.12	-0.11	**0.74**		
6	IA Knowledge (Yes)	0.00	0.07	-0.05	-0.19	0.10	-	
7	Performance Expectancy	0.65	-0.21	-0.09	0.05	0.27	-0.10	**0.91**

Note: N = 199; Square root of AVE (bolded cells); [1]1= "younger than 18 years old"; 2 = "19 to 29 years old"; 3 = "30 to 40 years old"; 4 = "41 to 50 years old"; 5 = "51 to 60 years old" and 6 = "61 or older".

Table A2. Construct Correlations