The Effects of Expertise, Humanness, and Congruence on Perceived Trust, Warmth, Competence and Intention to Use Embodied AI

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Figure 1: Erif, an expert AI that is embodied as a physician, helps participants diagnose and repair a robot arm.

ABSTRACT

Even though people imagine different embodiments when asked which AI they would like to work with, most studies investigate trust in AI systems without specific physical appearances. This study aims to close this gap by combining influencing factors of trust to analyze their impact on the perceived trustworthiness, warmth, and competence of an **embodied** AI. We recruited 68 participants who observed three co-working scenes with an embodied AI, presented as expert/novice (expertise), human/AI (humanness), or congruent/slightly incongruent to the environment (congruence). Our results show that the expertise condition had the largest impact on trust, acceptance, and perceived warmth and competence. When controlled for perceived competence, the humanness of the AI and the congruence of its embodiment to the environment also influence acceptance. The results show that besides expertise and the perceived competence of the AI, other design variables are relevant for successful human-AI interaction, especially when the AI is embodied.

CCS CONCEPTS

• **Computing methodologies → Intelligent agents**; • **Human-centered computing → Empirical studies in HCI**; *Interactive systems and tools*; *Visualization.*

KEYWORDS

Intelligent Agents, Trust, Technology Acceptance, Framing, Congruence, Visualization

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1 INTRODUCTION

Artificial intelligence (AI) gains in importance for individuals, organizations, and society [3, 50]. It is even called a part of the "fourth industrial revolution" [51]. AI is already integrated into various systems, tasks [6], and into various fields such as healthcare [61], hospitality services [29], or agriculture [20]. Despite the increasing use and the promising possibilities, people tend to mistrust AI systems, i.a., due to assumed privacy threats [27]. In Human-AI Interactions (HAII), research revealed determining factors of trust [16, 17, 21, 34], such as the perceived expertise (i.e., expert versus non-expert) and the perceived humanness (i.e., human versus AI) of an AI system [16, 18, 19].

Users prefer systems that are framed as experts [60] and follow an AI's advice more often if they are framed as humans [9, 33] or if the task has an objective best outcome [19, 33]. Of these trust cues, expert framing was shown to have the strongest effect [19]. However, the experimental tasks used in previous studies were rather abstract and only had a few consequences. The HAIIs were limited to AI interfaces that were located outside of the task's usual environment and context (e.g., input on a computer in a laboratory). Existing research, however, shows that when users were asked how they imagine AI systems with which they would like to work, the majority drew an AI system embodied in the context of the work task [52]. The embodiment of AI systems can take on various forms, which raises similar questions to its effects as digital human replicas (e.g., avatars) [31, 32, 59] or robots [35, 40, 62]. In these fields, studies showed that how the appearance of an embodied AI system is perceived is significantly influenced by whether it matches the digital human's behavior [35, 40] or the environment/context [38]. The congruence of appearance and context raises further questions about its impact on trust in AI systems, which have not been studied yet.

Addressing this gap in research, the following research questions arise: (1) To what extent do expert and humanness framing influence trust in embodied AI systems? (2) How does the (in)congruence between the appearance of an embodied AI and the interaction context affect trust in AI systems?

2 THEORETICAL BACKGROUND

2.1 Humanness and Expertise Framing as Trust Cues

Existing research shows that the traits of both the trust-giver and the recipient play a pivotal role in determining the degree of trust. In dyadic interactions, trust is defined as "the willingness to rely on and be vulnerable to another party" [55]. Studies on trust in human-human interactions highlighted three main attributes: competence, benevolence, and integrity [2, 39, 41]. These cues were shown to be also relevant in human-technology interactions [44, 47]. Neuroscientific studies indicated the activation of similar brain regions for both trust in humans and in technological systems [48, 57]. However, aspects of human-human trust are not always transferable to HAAI [4] and must be properly calibrated to avoid over- and undertrust [11], thus highlighting the need for further research on this topic.

To avoid confounding effects of the systems' performance, studies do not vary their actual performance, but the background story participants are presented with (framing) to investigate impact factors on trust. For example, test subjects are instructed to work with a specialized versus a generic system (**expert framing**) or with a human or a technological counterpart (**framing of humanness**). In a study by Logg et al. [33], participants had to complete rather analytical tasks such as estimating a person's weight, the attractiveness of women, and the popularity of songs. They received a recommendation, which was framed as either being generated by a real person or by an algorithm. Results revealed a preference for the algorithm. Castelo et al. [9] found a preference for algorithmic recommendations for tasks with an objectively correct outcome, like prediction of the weather or stocks, and a preference for human recommendations for tasks that may have nuances and multiple solutions, like diagnostics and controlling vehicles. Given the choice of whether they would rather work with a "qualified person" or an "algorithm" in diverse tasks, participants preferred the "qualified person". However, by using the phrase "qualified," the authors framed not only the humanness of the AI system but also its expertise.

Expertise serves as another strong cue of trust in both human-human [10, 23] and human-machine interactions [22, 28, 60]. Hou and Jung [19] investigated if the framing of both humanness and expertise interacts. Their literature review revealed that users prefer the advice of algorithms but only when they were presented as qualified, which already indicates the presence of an interaction effect. In a follow-up empirical study, they found a strong impact of expertise framing, which entirely negated the humanness framing. They found no effect of the task type ("analytical" versus "creative"). Thus, framing an AI as human and as an expert seems to be able to increase user trust in a system, with the expert cue having a stronger effect and being able to overshadow the effect of humanness framing.

2.2 Congruence between Embodiment and Context as Trust Cue

When asked how an AI people would like to work with should look, embodied systems were the most popular choice [8, 52]. Using embodied systems instead of text-based systems has been shown to have various benefits, like improving knowledge retention in learning [25], or improving the quality and naturalness of conversations [1, 24]. The design of these systems, i.e., the external appearance of avatars, agents, or robots, can have a massive influence on trust [31, 32, 35, 40, 59, 62]. Studies indicated the effect of appearance is significantly influenced by whether it matches the shown behavior [35, 40] or the environment/context [38].

In a study by Mal et al. [38], participants exercised in a virtual environment (fitness studio or office) while being embodied in an avatar wearing either sportswear or business attire. The avatar was evaluated as more plausible in the congruent condition. The authors, however, found no effect of congruence on performance. Lin et al. [30] found that the appearance of an avatar affected the participants' acceptance of the avatar's advice. In addition, outward appearances of avatars that were incongruent with the environment led to a decrease in trust [31]. In sum, the appearance of the embodiment

(a) Factory Worker (congruent) **(b) Office Worker (slightly incongruent)** **(c) Physician (incongruent)**

Figure 2: The embodied AI used in the experiment was either embodied as a factory worker (congruent to the environment), an office worker (slightly incongruent), or a physician (incongruent) with avatars derived from *Rocketbox* [14].

and the fit between embodiment and context have an effect on plausibility and advice acceptance.

2.3 Present Study and Contribution

Whether congruence is a relevant cue of trust in HAII and how it interacts with framing remains unclear. This study thus aims to close this research gap by combining influencing factors of trust to analyze their impact on the perceived trustworthiness, warmth, and competence of an **embodied** AI. We investigated the research questions with a between-subjects experiment where we manipulated (1) the framing of expertise (novice/expert), (2) the framing of humanness (colleague/AI), and (3) the congruence between the AI's embodiment and the environment (congruent/slightly incongruent). In an online study, 68 participants watched videos of a fictitious human-AI interaction in which the AI made suggestions about decisions in a factory setting (i.e., reconfiguring a production line, repairing a robot arm, and making HR decisions). We discussed that both framing the humanness [5, 9, 33] and the framing of expertise [19, 22, 28, 60] influences the acceptance of an AI's advice. We therefore derive *H1* and *H2*:

H1. The expertise of an AI significantly influences the users' acceptance, trust, perceived competence, and warmth.

H2. The humanness of an AI significantly influences the users' acceptance, trust, perceived competence, and warmth.

Prior work also revealed that the congruence between an AI's visual appearance and the virtual environment affects plausibility [8, 38, 60] and could, therefore, also affect other top-down processes like trust [26]. Thus, *H3* postulates:

H3. The congruence of the visual representation of AI to the virtual environment significantly influences the users' acceptance, trust, perceived competence, and warmth.

3 METHODS

3.1 Study Design and Procedure

We conducted a 2x2x3 between-design online study with expertise (novice/expert) and humanness (human/AI) framing and the congruence of the AI's visualization to the virtual environment (congruent/slightly incongruent/incongruent) as between factors. The study procedure is visualized in Figure 3. First, participants filled out consent forms and were randomly assigned to one of the experimental conditions. Then, they were instructed to imagine themselves in a particular scenario: It was their first day in their new job at a toy factory as the manager of the research & development department. They were provided with a digital mentor who would support them by giving advice. Participants had to complete three tasks: reconfigure a production line, diagnose why a robot arm fails, and make human resources decisions. To do so, they were instructed to read two documents: The HR department's notes about each colleague and a manual to repair and reconfigure the production line. Participants had seven and a half minutes to read the documents. This was not enough time to fully comprehend all the information, resulting in the participants' need to rely on the digital mentor's advice. After reading the texts, participants watched three video clips of a fictional conversation between themselves and the mentor (presented in random order). The mentor was shown standing in front of a production line. Figure 2 shows all three possible embodiments used for the digital mentor: a factory worker (congruent to the environment), an office worker (slightly incongruent), or a physician (incongruent). We chose those representations from the *Rocketbox* library [14] according to whom one would expect to work with in a factory: Working with a factory worker should be plausible while receiving help from an office worker or physician on how to repair a robot arm should be considered implausible. We simulated the participants' responses in the conversation with predefined text written in speech bubbles. At the end of each interaction, the mentor would advise following a course of action with a high risk of failure. After watching all three videos, participants completed a questionnaire and were compensated. We framed the humanness and expertise of the mentor thrice: before participants received the documents and before each video in written form, and at the start of each video verbalized by the mentor. The exact wording can be found in section C in the appendix.

3.2 Video Generation & Presentation

Across the videos, the environment, animations, perspective, lighting conditions, and background sounds were kept constant. Videos were generated using *Unity Engine 2021.3.11f1* [54] on a desktop PC with an Intel i9-12900K CPU, a Nvidia Geforce RTX 3090 GPU, and 64 GB of RAM. Avatars and animations from the *Rocketbox* library were used to embody the AI [14]. *Azure Text to Speech* was used for the speech synthesis of the AI [43], *Oculus Lipsync* for lip sync [42], and the *Rocketbox* library for gestures [14]. Videos were optimized for web streaming and stored in .mp4 format using *Handbrake 1.7.2* [53]. The experiment was presented in *SoSci Survey* [13].

3.3 Measures

Participants indicated their willingness to follow the mentor's advice ("The mentor has just given you a recommendation. How much would you like to follow the recommendation?") on a seven-point Likert scale ("Not at all" to "Completely") after every video interaction. We calculated a mean score. The internal consistency was low (α = .37). However, we decided to keep this exploratory scale to generate first insights in this early stage of research. All semantic differentials consisted of 7 gradations, including the extremes. *Acceptance* of the mentor was measured using three items of the *UTAUT* [56] asking for their intention to use the mentor in the future (e.g., "I intend to use this mentor in the future"). Answers were

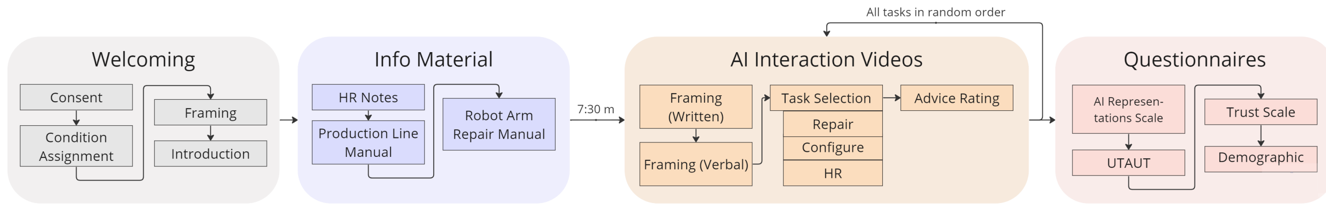

Figure 3: The study procedure: Participants watched three fictional human-AI interactions and filled in questionnaires.

given on a five-point Likert scale ("Strongly disagree" to "Strongly agree"). To assess the perceived *warmth*, *competence*, and *animacy* (control variable) of the mentor, the *AI Representations scale* by Straka et al. [52] was used. Warmth was rated on five semantic differentials (e.g., "Evil - Good", "Bad to me - Good to me"), competence on four (e.g., "Intelligent - Unintelligent", "Not useful - Useful"), and animacy on four (e.g., "Dead - Alive", "No own will/Own will"). We measured *trust* using the Human-Computer Trust Scale [36], including items such as "I believe that this mentor is acting in my best interests." or "When I use this mentor, I have the feeling that I can rely on it completely" on a five-point Likert scale ("Do not agree at all" to "Fully agree"). *Plausibility* (i.e., the match of the mentor with the virtual environment) was measured using the Virtual Human Plausibility Scale [37]. The participants answered four items (e.g., "The virtual character fitted into the virtual environment.", "The virtual character was a plausible part of the virtual environment.") on a seven-point Likert scale ("strongly disagree, disagree, somewhat disagree, neither, somewhat agree, agree, strongly agree"). All questionnaire scales showed a high internal consistency ($\alpha > .8$).

3.4 Data control

To confirm the experimental manipulation, participants needed to identify the mentor's embodiment at the end of the study. All participants correctly identified the embodiment in the congruent embodiment condition, and in the slightly incongruent condition, 90.91%. However, in the incongruent condition, the identification rate was much lower: only 42.86% of the participants identified the embodiment as a physician, whereas 54.26% identified it as a factory worker or food chemist. We assume that the perceived incongruence between the factory background and the embodiment as a physician was so strong that it did not fit the participants' internal model at all and that participants instead adopted a more plausible explanation: a food chemist or factory worker working on a task requiring protective clothing. We thus excluded the condition "incongruent" from further analysis and instead focused on the effects between the congruent and slightly incongruent conditions.

3.5 Participants

The sample consists of 103 participants contacted via Prolific [46]. They received 8 GBP for the completion of the study. Because of the data control described above, the sample size was reduced to 68 individuals. The following description of the sample refers to the participants that were kept for the analyses. In age, they ranged from 20 to 63 years, with a mean age of 34.26 years (SD = 10.33). 50.00% of the participants stated to be male, 48.53% female, and 1.47% other. All participants lived in Germany; most were born there (92.65%). They worked full-time (58.82%) or part-time (41.18%), with 29.41% of the participants stating to be students.

4 RESULTS

We used *R 4.3.2* [12] for data analysis with a significance level of $\alpha = .05$. A sum score was calculated for each scale. The average completion time of the study was 43.01 minutes (*SD* = 13.98, *median* = 40.17), with the fastest completion in 24.58 minutes and the slowest in 131.98 minutes. All participants answered every question. From four attention checks (e.g., "Please select 'Does not apply at all'".), sixteen participants failed the last. However, due to the overall high rate of correct answers, we did not exclude participants from the analyses due to failed attention checks.

To test the hypotheses, we first computed a three-way between-subject ANOVA for acceptance, warmth, competence, trust, and the following of advice. Levene tests indicated that the variances were equal in all conditions. Q-Q residual plots showed no strong deviations from normal distribution. Only expertise framing significantly affected the dependent variables (Table 1). Its effects on acceptance (η^2_{part} = .09), warmth (η^2_{part} = .11), and following of advice (η^2_{part} = .10) were medium, the effects on competence (η^2_{part} = .16) and on trust (η^2_{part} = .23) were large. Across all conditions, the values were higher for the expert condition compared to the novice condition (Table 2). To investigate the meaning of the significant interaction between Humanness and Congruence for the following of advice, we calculated Tukey multiple comparisons. However, we did not find any significant conditional effects ($p > .05$).

In an exploratory second step, we calculated mediation effects using lavaan [49] to better understand how the experimental manipulations might affect the dependent variables. We entered the dichotomous manipulations (Expertise, Humanness, and Congruence) as independent variables, the corresponding manipulations checks as mediators (competence as a mediator of expertise, animacy as a mediator of humanness, and plausibility as a mediator of the effect of congruence) on the dependent variables. Acceptance, warmth, trust, and the following of advice were entered as dependent variables in one path model. We estimated 1000 Bootstrap samples to test the significance of the indirect effects. The model was significant ($\chi^2(9) = 53.89$, $p < .001$, CFI = .85, RMSEA = .27 (95%-CI: .20, .34), SRMR = .21).

Expertise was a significant predictor of competence (competence was rated higher in the expert group compared to the novice group), and humanness significantly predicted animacy (animacy was rated higher in the human group compared to the AI group; see Table

Table 1: Results of the three-way ANOVAs with the dependent variables Acceptance, Warmth, Competence, Trust, and Following of advice (Advice)

	Acceptance		Warmth		Competence		Trust		Advice	
	F	*p*	*F*	*p*	*F*	p	*F*	*p*	*F*	*p*
Expertise	5.81	.019*	7.77	.007**	11.83	.001**	18.01	<.001***	6.70	.012*
Humanness	0.65	.425	0.29	.592	0.08	.777	0.10	.760	0.23	.637
Congruence	0.29	.593	0.55	.462	0.20	.656	1.24	.270	0.07	.788
Expertise*Humanness	0.22	.639	0.02	.883	0.15	.701	0.02	.895	1.65	.204
Expertise*Congruence	0.19	.665	0.91	.344	1.41	.239	1.55	.218	0.02	.889
Humanness*Congruence	0.00	.985	0.34	.561	0.49	.485	3.27	.076	8.73	.004**
Threeway Interaction	0.07	.789	1.29	.260	0.07	.794	0.04	.838	0.02	.882

Note. The degrees of freedom for all analyses are 1, 60.

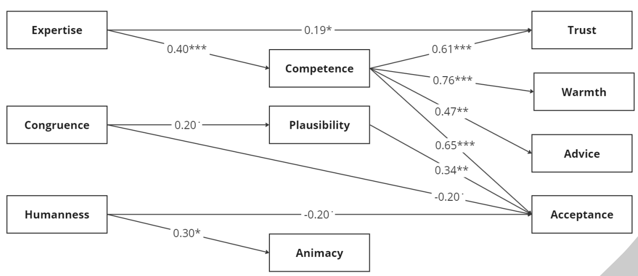

Figure 4: A visualization of the mediation model. We included only significant paths. For each of the paths, beta regression coefficients and significance are shown.

2). The congruence, however, was no significant predictor of the plausibility in any of the mediation analyses. Acceptance was significantly predicted by competence and plausibility and marginally significantly predicted by humanness (p = .061) and congruence (p = .057). The indirect effect of expertise on acceptance via competence was significant (Table 4). Competence was the only significant predictor of warmth. An indirect effect of expertise on warmth via competence was significant. Trust was significantly predicted by expertise and competence. Again, the indirect effect of expertise via competence was significant. Following of advice was significantly predicted by competence only. As for the other analyses, the indirect effect of expertise via competence was significant. Of the dependent variables, only trust and advice were significantly correlated. See Figure 4 for a visualization of these effects.

5 DISCUSSION

In this work, we investigated to what extent expert and humanness framing and (in)congruences between the appearance of an embodied AI and the interaction context influence trust in embodied AI systems. In line with *H1* and previous work, our results reveal the impact of the expertise framing of an AI system on its perceived trust, warmth, competence, and acceptance of its advice [19, 60]. In this study, the effect of expertise framing was large for trust, medium for competence, and small for warmth and acceptance. However, contrary to *H2* and *H3*, the type of the AI's embodiment and its congruence to the environment did not affect warmth, competence, and acceptance. There was no effect of the task on congruence as well. The additional mediation effects further clarify our results and show that perceived competence, in particular, has a decisive influence. It (completely) mediates the effects of expertise framing for trust (subjective and objective), warmth, and acceptance of AI. This overshadowing effect of expertise and perceived competence has also been shown in previous research [19]. Our results add the importance of controlling for this strong influencing factor since the effects of the other trust cues only came into play when perceived competence was controlled. We could show that the AI was more accepted when it was framed as a human and the embodiment was congruent with the environment (marginally significant) when controlling for perceived competence and plausibility. Thus, we partly accept *H2* and *H3*: Framing an AI's humanness and its embodiment's congruence to the environment can indeed influence the acceptance of an AI's advice, but only when controlling for perceived competence. These findings are particularly relevant in the context of AI use in workplaces and proper trust calibration [11]. It can be assumed that specific expert systems will be developed here, so that the design options for further trust cues are more interesting and offer opportunities for a human-centered design approach.

This study was the first to show that the fit of an embodied AI to the work environment can influence the acceptance of the AI, confirming similar results from other domains [34, 38, 40]. Congruence becomes increasingly important when AI systems collaborate with humans as embodied co-workers or team partners. In this context, the need for embodied technologies will become increasingly important [52], as embodiment is crucial to fulfilling basic human needs and the human principles of information processing and communication. The question arises about what other design variables are relevant to achieve successful human-AI interaction and build trust in AI, especially when the AI is embodied.

Overall, our results confirm the basic principles of the *Media Equation Approach* [44] postulating that interactions with technological counterparts resemble human-human interaction and can elicit social reactions that were originally exclusive to interpersonal encounters. Consequently, designers and developers responsible for implementing AI systems in organizations should be aware of these principles and their impact on the users of these systems.

5.1 Limitations and Future Work

Our study emphasizes the challenges of embodying AI systems. While the office worker was recognized well, the physician was not recognized with certainty. Future studies should explore further embodiments, considering users' expectations of e.g., abstract or machine-like systems [52]. Since different visualizations are cost-intensive to realize, this study used video vignettes. Unfortunately, this means that there are far fewer cues than in real HAII, e.g., the relation of space, the active interaction, or the feeling of really interacting with the AI in a room. Future work could use immersive testbeds to simulate HAII in virtual realities [59], resulting in increased involvement and more vivid incongruencies between the AI's embodiment and the environment [58].

Further, the internal consistency of the scale *following of advice* was low. Even though our continued use of the scale can be reasonably explained, future research should additionally use a more robust instrument and objective measures to assess if users followed the advice of the AI system. Also, implicit measures should be used to measure trust as these are more precise than self-reported trust measures [7, 15] and could thus further clarify these observations.

Our results are also limited by the task design. We designed the tasks - making HR decisions, repairing a robot arm, and reconfiguring a product line - to be plausible in a factory environment. Previous literature shows that the advice of AI systems was preferred in analytical tasks [9, 33] while characteristics usually attributed to humans, such as perceived benevolence, are decisive for moral decisions, and tasks with high emotional difficulty [2, 5]. Despite our attempts to provide a variety of tasks, participants might have had the impression of a certain objective best outcome, which is typical for analytical tasks. Future work should aim for a comprehensive overview of various tasks for human-AI interaction and relevant influencing factors to systematically vary tasks and attributes of the interaction partner and analyze the effects on trust.

Finally, our results may be limited by the participants' cultural background. Despite research showing that the perceived culture of an agent may affect how embodied AI is perceived [45], we purposely chose to recruit only German participants to ensure that the instructional material was well understood.

6 CONCLUSION

Our study was the first to investigate the (1) effects of expert and humanness framing as trust cues of *embodied* AI systems and (2) effects of (in)congruence between the appearance of an embodied AI and the context of the interaction influences trust in AI systems. To gain first insights, participants in an online study watched three fictional interactions where they received advice from an AI. We found that framing the AI's expertise and its perceived competence are the most important factors concerning the user's trust, warmth, and acceptance of the AI. Moreover, if controlled for perceived competence, the acceptance of an AI will be higher if it is introduced as human, if the embodiment is congruent with the environment of the interaction, and if it is more plausible. If we assume that expert systems are predominantly used in work contexts, the present study indicates that, besides expertise, design factors such as the congruence of the embodied AI's visual characteristics and the environment are worth examining in more detail. With AIs becoming more physically present in work contexts, optimizing their outward appearance will become increasingly important for successful human-AI interaction.

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A DESCRIPTIVE STATISTICS

Table 2: Descriptive statistics for the dependent variable acceptance, warmth, competence, and trust, following of advice, and the mediators animacy and plausibility

		n	Acceptance *M* (*SD*)	Warmth *M* (*SD*)	Competence *M* (*SD*)	Trust *M* (*SD*)	Advice *M* (*SD*)	Animacy *M* (*SD*)	Plausibility *M* (*SD*)
Expert									
Human	Congruent	9	11.67 (2.83)	32.89 (7.24)	24.67 (2.78)	44.00 (4.27)	14.78 (4.12)	20.44 (5.32)	23.78 (4.87)
	Incongruent	8	12.13 (2.95)	33.88 (3.48)	24.88 (2.10)	42.13 (3.40)	11.88 (2.42)	16.75 (3.33)	24.25 (1.98)
	Total	17	11.88 (2.80)	33.35 (5.63)	24.76 (2.41)	43.12 (3.89)	13.41 (3.64)	18.71 (4.75)	24.00 (3.69)
AI	Congruent	9	12.33 (1.41)	33.00 (4.53)	24.33 (2.69)	41.56 (4.30)	13.67 (3.39)	15.22 (3.53)	23.33 (4.15)
	Incongruent	9	13.11 (1.83)	32.56 (6.37)	25.33 (3.00)	43.56 (3.00)	16.11 (2.47)	12.33 (4.74)	21.67 (5.52)
	Total	18	12.72 (1.64)	32.78 (5.36)	24.83 (2.81)	42.56 (3.75)	14.89 (3.14)	13.78 (4.32)	22.50 (4.82)
Total	Congruent	18	12.00 (2.20)	32.94 (5.86)	24.50 (2.66)	42.78 (4.35)	14.22 (3.70)	17.83 (5.14)	23.56 (4.40)
	Incongruent	17	12.65 (2.40)	33.18 (5.10)	25.12 (2.55)	42.88 (3.18)	14.12 (3.22)	14.41 (4.61)	22.88 (4.33)
	Total	35	12.31 (2.29)	33.06 (5.42)	24.80 (2.59)	42.83 (3.77)	14.17 (3.43)	16.17 (5.12)	23.23 (4.31)
Novice									
Human	Congruent	8	10.50 (2.45)	32.13 (3.72)	23.25 (2.71)	40.50 (4.17)	13.75 (3.06)	15.50 (3.85)	22.75 (2.43)
	Incongruent	8	10.75 (3.41)	27.25 (7.38)	20.88 (5.14)	35.13 (2.90)	10.88 (3.72)	11.00 (5.15)	20.13 (5.57)
	Total	16	10.63 (2.87)	29.69 (6.18)	22.06 (4.15)	37.81 (4.45)	12.31 (3.61)	13.25 (4.97)	21.44 (4.37)
AI	Congruent	9	10.89 (2.98)	28.78 (4.94)	21.78 (4.12)	37.89 (9.18)	10.67 (4.39)	11.44 (4.33)	23.00 (7.81)
	Incongruent	8	10.75 (3.37)	28.75 (6.25)	21.13 (5.38)	37.38 (4.93)	12.63 (4.21)	12.38 (7.01)	18.63 (6.19)
	Total	17	10.82 (3.07)	28.76 (5.41)	21.47 (4.61)	37.65 (7.27)	11.59 (4.29)	11.88 (5.58)	20.94 (7.23)
Total	Congruent	17	10.71 (2.66)	30.35 (4.61)	22.47 (3.50)	39.12 (7.18)	12.12 (4.03)	13.35 (4.50)	22.88 (5.75)
	Incongruent	16	10.75 (3.28)	28.00 (6.65)	21.00 (5.09)	36.25 (4.07)	11.75 (3.94)	11.69 (5.99)	19.38 (5.74)
	Total	33	10.73 (2.93)	29.21 (5.73)	21.76 (4.34)	37.73 (5.98)	11.94 (3.93)	12.55 (5.26)	21.18 (5.93)
Total									
Human	Congruent	17	11.12 (2.64)	32.53 (5.69)	24.00 (2.76)	42.35 (4.47)	14.29 (3.58)	18.12 (5.21)	23.29 (3.84)
	Incongruent	16	11.44 (3.16)	30.56 (6.54)	22.88 (4.32)	38.63 (4.73)	11.38 (3.07)	13.88 (5.14)	22.19 (4.56)
	Total	33	11.27 (2.86)	31.58 (6.10)	23.45 (3.59)	40.55 (4.91)	12.88 (3.61)	16.06 (5.53)	22.76 (4.18)
AI	Congruent	18	11.61 (2.38)	30.89 (5.09)	23.06 (3.62)	39.72 (7.21)	12.17 (4.11)	13.33 (4.30)	23.17 (6.07)
	Incongruent	17	12.00 (2.85)	30.76 (6.42)	23.35 (4.68)	40.65 (5.02)	14.47 (3.74)	12.35 (5.72)	20.24 (5.87)
	Total	35	11.80 (2.59)	30.83 (5.69)	23.20 (4.11)	40.17 (6.17)	13.29 (4.05)	12.86 (4.99)	21.74 (6.07)
Total	Congruent	35	11.37 (2.49)	31.69 (5.37)	23.51 (3.22)	41.00 (6.10)	13.20 (3.95)	15.66 (5.28)	23.23 (5.04)
	Incongruent	33	11.73 (2.97)	30.67 (6.38)	23.12 (4.44)	39.67 (4.92)	12.97 (3.73)	13.09 (5.42)	21.18 (5.29)
	Total	68	11.54 (2.72)	31.19 (5.86)	23.32 (3.84)	40.35 (5.56)	13.09 (3.82)	14.41 (5.46)	22.24 (5.22)

B MEDIATION ANALYSIS

Table 3: Regression effects of the mediation analysis using lavaan

DV	R^2	IV	b	β	SE	z	p
Competence	.16	Expertise	3.04	0.40	0.87	3.51	$< .001^{***}$
Animacy	.09	Humanness	3.20	0.30	1.26	2.54	$.011^{*}$
Plausibility	.04	Congruence	2.05	0.20	1.24	1.65	.099
Acceptance	.58	Expertise	-0.13	-0.03	0.47	-0.27	.786
		Humanness	-0.93	-0.20	0.50	-1.86	.063
		Congruence	-0.95	-0.20	0.51	-1.88	.060
		Competence	0.41	0.65	0.10	4.19	$< .001^{***}$
		Animacy	0.05	0.10	0.06	0.77	.440
		Plausibility	0.16	0.34	0.05	3.07	$.002^{**}$
Warmth	.61	Expertise	-0.17	-0.02	1.06	-0.16	.872
		Humanness	-0.18	-0.02	0.92	-0.19	.848
		Congruence	-0.07	-0.01	0.84	-0.09	.930
		Competence	1.04	0.76	0.18	5.75	$< .001^{***}$
		Animacy	0.17	0.17	0.12	1.44	.151
		Plausibility	0.13	0.13	0.14	0.94	.347
Trust	.58	Expertise	1.84	0.19	0.82	2.26	$.024^{*}$
		Humanness	-0.45	-0.05	0.76	-0.59	.556
		Congruence	0.27	0.03	0.97	0.28	.779
		Competence	0.78	0.61	0.17	4.62	$< .001^{***}$
		Animacy	0.13	0.14	0.09	1.49	.137
		Plausibility	0.21	0.22	0.17	1.25	.212
Advice	.29	Expertise	0.99	0.13	0.89	1.11	.268
		Humanness	-0.36	-0.05	0.82	-0.44	.661
		Congruence	0.18	0.02	0.91	0.20	.842
		Competence	0.47	0.47	0.17	2.86	$.004^{**}$
		Animacy	-0.05	-0.08	0.10	-0.56	.578
		Plausibility	0.00	0.00	0.13	0.01	.995

Note. IV = independent variable, DV = dependent variable, SE = Standard Error

Table 4: Indirect effects of the mediation analysis using lavaan

IV	MV	DV	b	ci.lower	ci.upper	β	SE
Expertise	Competence	Acceptance	1.23	0.40	2.46	0.26	0.51
Humanness	Animacy	Acceptance	0.15	-0.15	0.77	0.03	0.22
Congruence	Plausibility	Acceptance	0.32	-0.02	0.87	0.07	0.22
Expertise	Competence	Warmth	3.15	1.45	5.47	0.30	1.02
Humanness	Animacy	Warmth	0.53	-0.13	1.76	0.05	0.49
Congruence	Plausibility	Warmth	0.26	-0.17	1.37	0.02	0.38
Expertise	Competence	Trust	2.37	1.17	3.91	0.24	0.70
Humanness	Animacy	Trust	0.41	-0.01	1.40	0.04	0.32
Congruence	Plausibility	Trust	0.43	-0.08	1.69	0.04	0.39
Expertise	Competence	Advice	1.44	0.62	2.53	0.19	0.49
Humanness	Animacy	Advice	-0.17	-1.09	0.37	-0.02	0.35
Congruence	Plausibility	Advice	-0.00	-0.73	0.52	-0.00	0.33

Note. IV = independent variable, MV = mediator variable, DV = dependent variable, SE = Standard Error.
A 95% confidence interval was estimated using 1000 bootstrap samples.

C FRAMINGS

All framings were translated from German to English.

C.1 Introductory Framing/Before each video

AI - Expert. You will be supported by Erif, a specialized expert tool. This tool was developed by experts from your company to provide you with optimum support in your activities. It can draw on many years of experience and decisions of your predecessors. By specializing in your area and the high quality of the data, it stands out from competing products and conventional chatbots.

Human - Expert. You will be supported by Erif, a colleague who specializes in your field of activity. This colleague is an expert in your company and will provide you with optimum support in your activities. He can draw on many years of experience and decisions. His specialization in your field and the high quality of his knowledge will set him apart from other colleagues.

AI - Novice. You will be supported by Erif, a general tool. This tool was developed by a trainee from your company to support you in your activities. It can draw on the recent experiences and decisions of your predecessors. Due to the generalization to different areas and the average quality of the data, it is comparable to competing products and conventional chatbots.

Human - Novice. You will be supported by Erif, a colleague. This colleague has not been with your company for long and will support you in your activities. He can draw on recent experience and decisions. Due to the generalization to different areas and the average quality of his knowledge, he is therefore comparable to other colleagues.

C.2 At the start of each video

AI - Expert. Hello! I am Erif, a specialized expert tool. I was trained by experts for this task and can draw on many years of experience and decisions made by your predecessors, which sets me apart from competing products.

Human - Expert. Hello! I am Erif, an expert and specialized in this field of activity. I can draw on many years of experience and decisions, which sets me apart from other colleagues.

AI - Novice. Hello! I am Erif, a general AI tool. I was trained by an intern for general tasks and can draw on recent experiences and decisions made by your predecessors, making me comparable to competing products.

Human - Novice. Hello! I'm Erif, a colleague. I am new to this field of activity. I can draw on recent experience and decisions, and am comparable to other colleagues.

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