Negative Perceptions of Outsourcing to Artificial Intelligence

Scott Claessens, Pierce Veitch, and Jim A.C. Everett

School of Psychology, University of Kent

Author Note

Scott Claessens https://orcid.org/0000-0002-3562-6981

Pierce Veitch https://orcid.org/0009-0005-3364-7470

Jim A.C. Everett https://orcid.org/0000-0003-2801-5426

All data and original code can be found on GitHub at https://github.com/ScottClaessens/outsourcing. The authors have no conflicts of interest to disclose. This work was generously supported by funding from the Horizon Europe UK Guarantee via the UKRI (EP/Y00440X/1) and a Philip Leverhulme Prize (PLP-2021-095) awarded to JACE. Author roles were classified using the Contributor Role Taxonomy (CRediT; https://credit.niso.org/) as follows: Scott Claessens: conceptualization, data curation, formal analysis, investigation, methodology, visualization, writing, editing; Pierce Veitch: formal analysis, methodology, editing; Jim A.C. Everett: conceptualization, funding acquisition, methodology, supervision, editing

Correspondence concerning this article should be addressed to Jim A.C. Everett, School of Psychology, University of Kent, Keynes College, Canterbury CT2 7NP, UK, Email: j.a.c.everett@kent.ac.uk

Abstract

As artificial intelligence (AI) tools become increasingly integrated into daily life, people are beginning to outsource not only professional tasks but also socio-relational ones. Large language models like ChatGPT can generate wedding vows, speeches, and personal messages, raising questions about how individuals who use AI for such tasks are perceived by others. In this paper, we conduct five pre-registered studies with British participants (N = 3,649) to understand how people view those who outsource tasks to AI, and how this depends on how socio-relational the task is, whether AI is used as a tool or fully delegated to, and the acknowledgment of the AI use. We find negative perceptions of outsourcing, particularly for socio-relational tasks. We show that outsourcing makes us think more negatively about not only the person and their motivations, but also the outsourced work itself. Moreover, we provide insight into why this occurs: the reduced effort from outsourcing socio-relational tasks to AI signals that the output is less authentically one's own and that the person cares less about the task. Our research highlights the way that AI use shapes our perceptions of people, raising key philosophical questions about efficiency, authenticity, and social ties in a world filled with AI-mediated interactions.

Keywords: artificial intelligence, person perception, outsourcing, trust

Negative Perceptions of Outsourcing to Artificial Intelligence

The widespread release of generative AI language models has transformed daily life, offering the potential to perform a variety of tasks more efficiently and, in some cases, with greater effectiveness than by doing them oneself. But as AI becomes more widely available, people are not only using it to assist them with things like preparing dinner recipes, writing data analysis code, and planning daily schedules. Increasingly, AI might be used beyond routine or technical domains to instead assist in tasks that are more socio-relational in nature, like writing wedding vows, apology notes, and love letters. Anecdotal evidence suggests that not only is AI-outsourcing of this kind already happening, but that it potentially has serious effects on how we judge others. In a recent Reddit post, a disgruntled newlywed tells the story of her husband using ChatGPT to write his wedding vows, expressing her discomfort with outsourcing something to AI that, to her, is deeply meaningful and a reflection of their love for one another (miramar0, 2024). Outsourcing tasks – especially socio-relational ones – to AI tools may be efficient, but could have negative consequences for person perception.

There is nothing new, in principle, about outsourcing tasks. For hundreds of years, personal assistants have organised daily schedules, recipe-books have provided meal plans, and guidebooks have created travel itineraries. In the socio-relational domain, ghostwriters have long-existed, and the internet is abound with professional paid services for writing wedding vows and personal speeches. AI merely supercharges what is an ancient human impulse: the push to reduce mental energy by outsourcing parts of our work onto people, books, tools, or systems. But even if outsourcing is an old phenomenon, the rapid shift in availability and use of AI models has fundamentally changed the ease with which people can outsource work, what kinds of tasks they can outsource, and the way in which they can outsource. These new developments in society mean that even as an old phenomenon in new clothes, there is much we still need to know about outsourcing.

First, we need to know how people who outsource tasks to AI are perceived. We know that people are increasingly using large language models (LLMs) for a wide variety of tasks

(Department for Science, Innovation & Technology, 2024). Due to their ubiquity, perhaps outsourcing to LLMs might not lead to negative perceptions? We are sceptical. We know that people dislike it when others "free ride" or reduce effort while benefiting from collective resources (e.g. Cubitt et al., 2011; Kerr, 1983) and that people's outputs are perceived as more valuable the more effort was ostensibly put into them (Kruger et al., 2004). Moreover, exertion of effort is deemed morally admirable and is rewarded, even in situations where effort does not directly generate additional product, quality, or economic value, suggesting that effort itself is moralised (Celniker et al., 2023). Given this, even if AI tools are widely available and pitched as improving efficiency, the core social psychological processes are likely to remain: someone is expending less effort to achieve a task, and people value effort. Indeed, some work shows that describing someone as using AI for a relational task led to the perception they expended less effort and were less satisfied with their relationship (Liu et al., 2024) and other unpublished work looking at perceptions of people using AI to complete academic assignments finds that using AI leads to more negative perceptions of moral character and suitability as a partner (Roth & Tissot, 2025).

Second, we need to know whether the *type* of task that people are outsourcing matters. One might expect outsourcing to be perceived negatively regardless of the type of task being outsourced – if effort is generally moralised, then the domain in which it is expended (or not) should have little impact. However, there are reasons to expect differences between social tasks like writing vows and non-social tasks like writing computer code. We know that different norms, standards, and expectations can be applied to social and non-social tasks and exchanges (e.g. A. P. Fiske, 1992; Heider, 1958; Malle, 2022). Moreover, from a philosophical perspective, it often matters not only *whether* something is done, but *how* it is done (Stohr, 2006). An apology is not just about hearing someone say "I am sorry", but seeing genuine regret; a love letter is not just about hearing someone say "I love you", but seeing depth of emotion; and a bereavement letter is not just about hearing someone say "I am sorry for your loss", but seeing an understanding for the powerful human experience of loss. There is, perhaps especially for social tasks, value not only in the outcome of doing something, but the *process* too (Goodman, 2010). To understand any potential negative effects of outsourcing to AI, we must therefore look at a broad range of non-social and social tasks, rather than draw broad conclusions based on a few use cases.

Third, we need to know how different ways of outsourcing to AI influence negative perceptions. Someone who "fully" outsources a task to AI by simply giving it a prompt and copying the output word-for-word might be perceived very differently to someone who gives the AI a prompt, revises the work accordingly, and finishes it themselves – using AI as a *collaborative tool*, rather than as a replacement. Similarly, someone could deceive others about their use of AI or be perfectly honest about it. While it seems reasonable to assume that "fully" outsourcing would be perceived worse than using AI as a tool, and that not acknowledging AI use would be perceived worse than being honest about it, it remains unclear how much this reduces negative perceptions: if someone uses AI in the "best" way, by using it as a collaborative tool and being open about this use, would they still suffer negative social consequences from doing so?

Fourth, we need to know how outsourcing to AI, in different kinds of tasks and in different ways, may shape different *kinds* of social perceptions. People can judge others on separate dimensions of warmth and competence (e.g. Abele et al., 2021; S. T. Fiske et al., 2007) as well as on dimensions of morality and trustworthiness (Goodwin et al., 2014). It remains unclear how outsourcing to AI might lead to differential character judgments across these different dimensions.

Fifth, we need to understand *why* outsourcing to AI, and therefore expending less effort, might have these effects. Previous work has focused on how expending less effort leads to negative perceptions of others (Celniker et al., 2023). But this raises the question of *why* effort is seen as important and what exactly it is signalling to others, beyond one's general cooperative intent. It is possible that outsourcing leads to negative perceptions because the lack of effort spent on the task signals something more fundamental about how authentic one is and how much one cares about the task: when someone chooses to outsource a love letter to an AI, they might be seen as valuing that love letter and what it represents less. It could be this second-step order of perceptions that is the key driver of negative perceptions, especially for socio-relational tasks.

Present Research

In this paper, we build on classic social psychological work on character inferences from reduced effort to understand how people view others who outsource different kinds of tasks, in different ways, for different reasons, to AI. Across five pre-registered experiments with British participants, we seek not only to understand how reduced effort through AI-outsourcing might shape perceptions of others, but also to understand in more depth *why* it is that reduced effort has the effect that it does.

In our initial pilot studies to motivate this work, we found that people who outsource a range of tasks to AI or another person are perceived more negatively than people who complete the tasks by themselves (see Supplementary Materials). In Study 1, we look at the effects of task type, AI use, and honesty. We explore how people perceive others who outsource different kinds of tasks with different levels of social relevance (e.g., from daily schedules, computer code and dinner recipes to wedding vows, apology letters, or bereavement cards), manipulating whether people use AI as a collaborative tool or “fully” outsource to AI and whether they are honest or deceptive about their use of AI. After turning to look at perceptions of both outsourcers and the outsourced work in Study 2, in Studies 3-5 we probe why outsourcing may have negative effects on how we evaluate others. In Study 3, we test potential mechanisms of perceived effort and authenticity by looking at how people evaluate others who either spend a lot or little time crafting the AI prompts, and who either outsource to a generic or personalised AI. In Study 4, we test the potential mechanism of perceived importance in the task by manipulating people’s reasons for using AI – either because they wanted to save time or because they cared about the task and thought that AI would improve their work. Finally, in Study 5, we bring these different potential mechanisms together to explore the different pathways that influence the relationship between outsourcing and negative perceptions, focusing on perceived effort, authenticity, and care in the task.

Study 1

Methods

Ethical Approval

Ethical approval was granted for all studies in this paper by the University of Kent's Psychology Research Ethics Panel. Participants in all studies provided informed consent and were debriefed after the study.

Participants

We conducted a power simulation to determine our target sample size. The simulation suggested that a sample size of 150 participants per condition (overall n = 750 for five conditions) would be required to detect a small difference between conditions (Cohen's $d \approx 0.20$) with above 80% power.

We recruited a convenience sample of 800 participants from the United Kingdom through the online platform Prolific (https://www.prolific.com/). After excluding participants who failed our pre-treatment attention check, we were left with a final sample of 762 participants (438 female; 316 male; 4 non-binary / third gender; 4 undisclosed gender; mean age = 42.16 years). 78% of these participants reported having used ChatGPT before (see Supplementary Figure 1).

Design

We used a "control plus 2x2" between-subjects design. Participants were randomly allocated to either the control condition, in which people in the scenarios complete the tasks themselves, or one of four experimental conditions, in which people in the scenarios use AI to complete the tasks. In the experimental conditions, we manipulated whether people in the scenarios used AI as a collaborative tool or "fully" outsourced to AI, and whether people were honest or deceptive about their use of AI. This resulted in five conditions overall: (*i*) the control condition, (*ii*) the tool-honest condition, (*iii*) the tool-deception condition, (*iv*) the full-honest condition, and (*v*) the full-deception condition.

Procedure

We presented participants with six scenarios. Each scenario described a person completing a task, such as writing computer code or writing a love letter. The six tasks were randomly drawn from a larger set of 16 tasks (see Supplementary Table 1 for the full list of tasks). For each scenario, we first told participants:

- *Control condition*: "In order to complete this task, [the person] works on it by themselves from start to finish."
- *Tool outsourcing conditions*: "In order to complete this task, [the person] uses the AI tool ChatGPT. They ask ChatGPT to provide ideas, inspiration, and feedback, but they edit and rewrite the suggestions and finish the task themselves."
- *Full outsourcing conditions*: "In order to complete this task, [the person] uses the AI tool ChatGPT. They copy ChatGPT's output word-for-word, rather than doing it themselves."

We then told participants in the experimental conditions:

- *Honest conditions*: "After completing the task, [the person] is asked how they came up with their ideas. [The person] acknowledges that they used ChatGPT as a tool / got ChatGPT to do the task for them."
- *Deception conditions*: "After completing the task, [the person] is asked how they came up with their ideas. [The person] does not acknowledge that they used ChatGPT as a tool / got ChatGPT to do the task for them."

We then asked participants how well each of the following words described the person in the scenario: competent, warm, moral, lazy, and trustworthy. Participants answered these questions on 7-point Likert scales, ranging from "does not describe [the person] well" to "describes [the person] extremely well".

After the six scenarios, we asked participants several questions about the AI tool ChatGPT, including their familiarity with ChatGPT, whether they had used ChatGPT before, how frequently they used ChatGPT, and how trustworthy they thought ChatGPT was (see Supplementary Figure 1).

Pre-registration

We pre-registered the study on the Open Science Framework (https://osf.io/knswr).

Statistical Analysis

We fitted Bayesian multivariate multilevel cumulative-link ordinal models to the data using the *brms* R package (Bürkner, 2017). We modelled each character evaluation – competence, warmth, morality, laziness, and trustworthiness – as a separate response variable and included fixed effects for conditions, varying intercepts for participants, and varying intercepts and slopes for tasks. We used regularising priors for all parameters to impose conservatism on parameter estimates. All models converged normally ($\hat{R} \leq 1.01$).

Transparency and Openness

For all studies in this paper, we report how we determined our sample size, all data exclusions, all manipulations, and all measures in the studies. All studies were pre-registered. Analyses for all studies were conducted in R v4.4.2 (R Core Team, 2022). Visualisations were produced using the *ggplot2* and *patchwork* packages (Pedersen, 2025; Wickham, 2016). The manuscript was reproducibly generated using the *targets* package (Landau, 2021) and *quarto* (Allaire et al., 2024). All data and code to reproduce the analyses and figures in this paper can be found here: https://github.com/ScottClaessens/outsourcing

Results

We first looked at the overall results averaging over tasks. Across all five character evaluations, we found that fully outsourcing to AI (i.e., copying the AI output verbatim) was perceived more negatively than using AI as a collaborative tool (Figure 1; Table 1). By contrast, we found that deception about AI usage had specific negative effects on perceptions of morality and trustworthiness: people who did not acknowledge their use of AI were perceived as less moral and less trustworthy. We did not find any interaction effects between full outsourcing and deception.

Table 1

Overall Pairwise Contrasts in Study 1

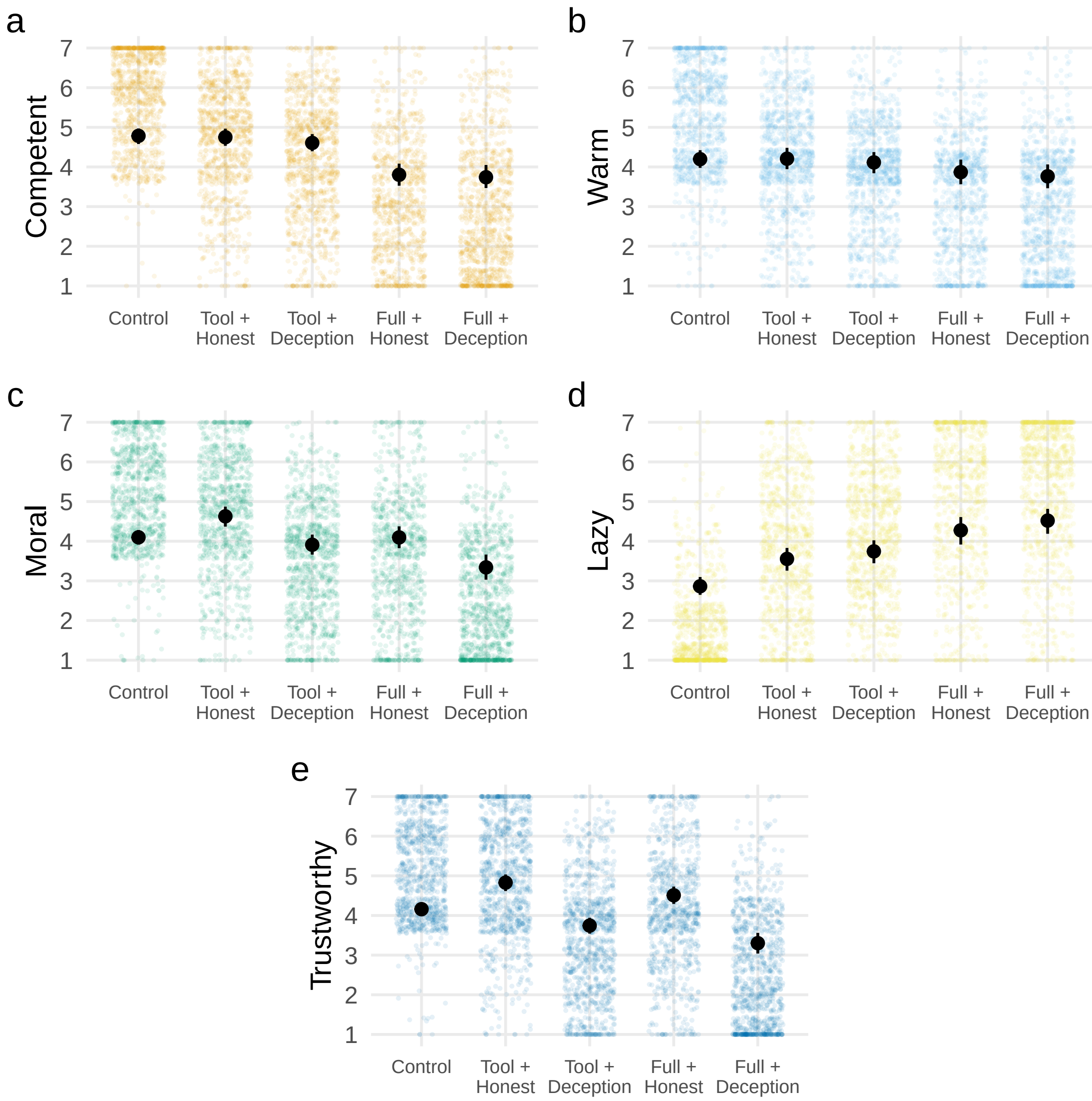
	Response				
	Competent	Warm	Moral	Lazy	Trustworthy
Comparison to control					
Tool Honest - Control	-0.04 [-0.25 0.19]	0.01 [-0.22 0.25]	0.53 [0.28 0.76]	0.69 [0.37 1.01]	0.67 [0.45 0.88]
Tool Deception - Control	-0.18 [-0.42 0.07]	-0.09 [-0.31 0.15]	-0.19 [-0.41 0.05]	0.88 [0.55 1.20]	-0.42 [-0.62 -0.20]
Full Honest - Control	-0.98 [-1.25 -0.71]	-0.33 [-0.59 -0.07]	-0.01 [-0.27 0.27]	1.42 [1.03 1.77]	0.35 [0.13 0.58]
Full Deception - Control	-1.05 [-1.33 -0.75]	-0.43 [-0.69 -0.16]	-0.76 [-1.04 -0.47]	1.66 [1.28 2.00]	-0.86 [-1.11 -0.59]
Effect of full outsourcing					
Full Honest - Tool Honest	-0.94 [-1.26 -0.63]	-0.34 [-0.64 -0.03]	-0.53 [-0.87 -0.20]	0.72 [0.29 1.14]	-0.32 [-0.60 -0.03]
Full Deception - Tool Deception	-0.87 [-1.18 -0.52]	-0.36 [-0.66 -0.02]	-0.57 [-0.91 -0.24]	0.78 [0.35 1.17]	-0.44 [-0.73 -0.15]
Effect of deception					
Tool Deception - Tool Honest	-0.14 [-0.42 0.13]	-0.09 [-0.39 0.20]	-0.72 [-1.01 -0.40]	0.19 [-0.19 0.58]	-1.08 [-1.35 -0.81]
Full Deception - Full Honest	-0.06 [-0.41 0.31]	-0.11 [-0.43 0.24]	-0.76 [-1.12 -0.38]	0.24 [-0.21 0.69]	-1.21 [-1.52 -0.89]
Interaction effect					
Interaction effect	0.08 [-0.36 0.53]	-0.01 [-0.45 0.43]	-0.03 [-0.51 0.42]	0.06 [-0.55 0.64]	-0.12 [-0.53 0.28]

Note. Numbers reflect differences in marginal means on a 7-point Likert scale, pooling over participants and tasks. The bottom row represents the interaction between full outsourcing and deception (i.e., the difference between the differences in the rows above). Main numbers are posterior medians, numbers in the square brackets are 95% credible intervals.

The effects of outsourcing to AI varied across the different tasks, especially for perceptions of warmth and morality (Figure 2). For example, people who used AI for social tasks, such as writing an apology letter or a bereavement card, were perceived as less warm, less moral, and lazier compared to people who completed the task themselves. This was true even if the person used AI as a tool and was honest about their usage of AI. By contrast, we observed weaker effects of outsourcing for non-social tasks like writing computer code or planning a syllabus.

Figure 1

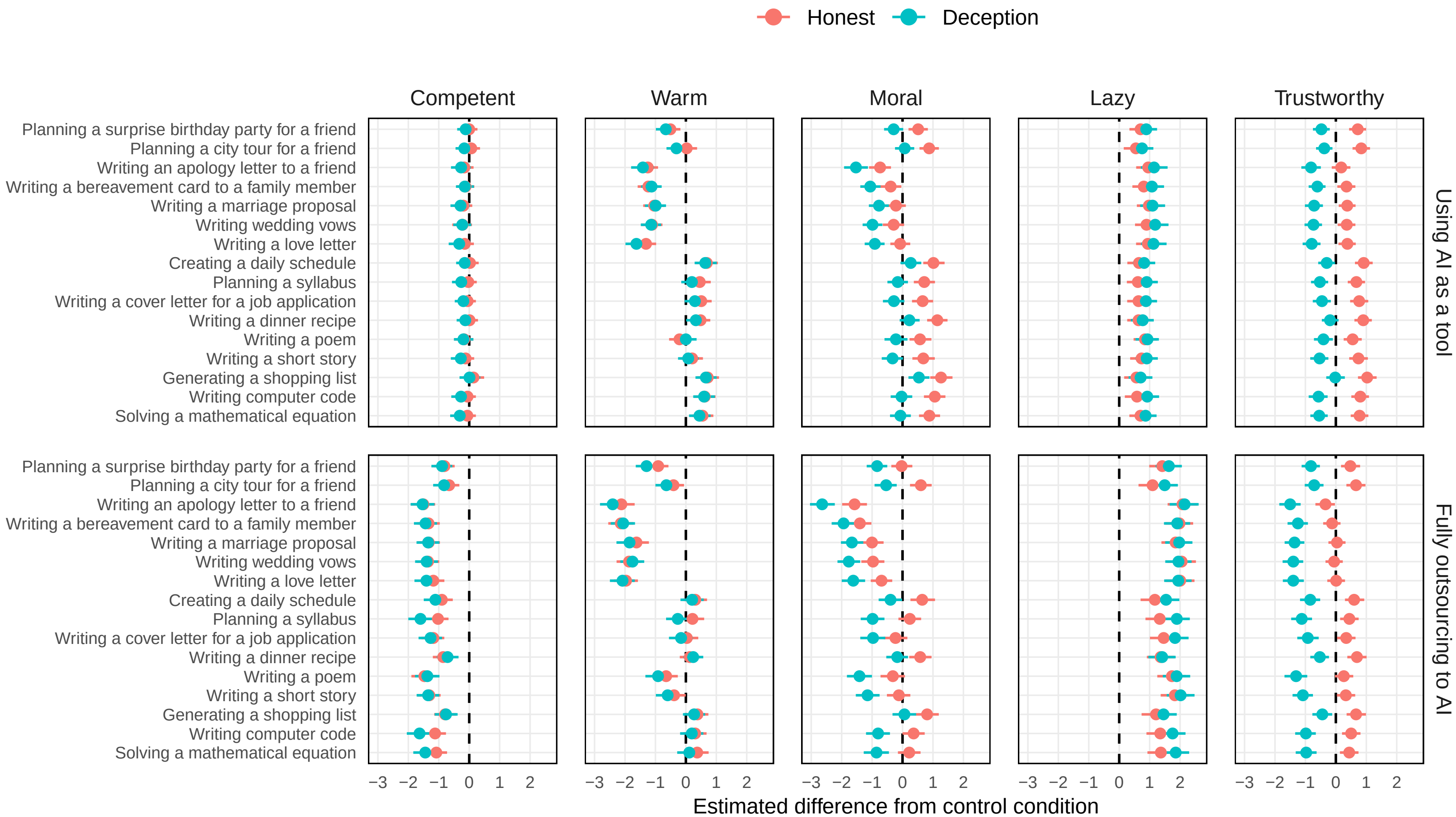
Overall Character Evaluations in Study 1



Note. Participants in the control condition and four AI outsourcing conditions evaluated people in the scenarios on (a) competence, (b) warmth, (c) morality, (d) laziness, and (e) trustworthiness. Coloured points represent participant responses to the questions, jittered for easier viewing. Black points are estimated marginal means from the fitted model, pooling over participants and tasks. Black points and line ranges represent posterior medians and 95% credible intervals, respectively.

Figure 2

Variation in the Effects of Outsourcing across Tasks in Study 1



Note. Tasks are ordered from most social (top) to least social (bottom) according to ratings from a pilot study. Point ranges are differences in marginal means on a 7-point Likert scale for the honest conditions (red) and deception conditions (blue) compared to the control condition. Upper panels refer to the tool outsourcing conditions, and lower panels refer to the full outsourcing conditions. Points and ranges represent posterior medians and 95% credible intervals, respectively.

To determine the factors that predict variation across tasks, we incorporated ratings of tasks from a pilot study (see Supplementary Materials for details). Participants were asked to rate the different tasks on several features: whether the task is social, requires social skills, impacts others, has important consequences, and requires effort. All of these features predicted stronger causal effects of outsourcing to AI compared to the control (Supplementary Figures 2 and 3). In other words, outsourcing to AI is perceived more negatively for tasks that have these features, compared to tasks without these features.

Discussion

In Study 1, we looked at how people who outsourced to AI in different ways were perceived across a broad range of social and non-social tasks. In line with our predictions, we found that "fully" outsourcing to AI was perceived more negatively than using AI as a collaborative tool, particularly for socio-relational tasks. We also found, predictably, that people were seen as less moral and less trustworthy if they did not acknowledge their use of AI. Importantly, though, we show that even using AI in the "best" way – only as a tool and being honest about one's usage – still led to negative social perceptions for the more socio-relational tasks like writing a love letter, an apology, or wedding vows.

In Study 2, we investigate whether these negative perceptions extend to the work itself and remain after seeing the output. It could be, for example, that someone is perceived badly for using ChatGPT to write their bereavement card, but the writing itself is seen as equally well-written and authentic, if not more so, than if the person had written the card themselves. Indeed, evidence suggests that text generated by ChatGPT is rated as higher quality than human-written text (Noy & Zhang, 2023). Moreover, it is possible that seeing appropriate output could mitigate negative perceptions by highlighting how the AI can in fact perform the task well. We explored these possibilities in Study 2.

Study 2

Methods

Participants

We conducted a power simulation to determine our target sample size. The simulation suggested that a sample size of 125 participants per condition (overall n = 750 for six conditions) would be required to detect a small-to-medium difference between conditions (Cohen's $d \approx 0.40$) with above 80% power.

We recruited a convenience sample of 800 participants from the United Kingdom through Prolific. After excluding participants who failed our pre-treatment attention check, we were left with a final sample of 766 participants (425 female; 337 male; 3 non-binary / third gender; 1 undisclosed gender; mean age = 41.93 years). 72% of these participants reported having used ChatGPT before (see Supplementary Figure 4).

Design

We randomly allocated participants to one of six conditions in a 3x2 between-subjects design. We manipulated the type of outsourcing: (*i*) no outsourcing control, (*ii*) using AI as a tool, and (*iii*) fully outsourcing to AI. Here, in contrast to Study 1, we also explicitly manipulated whether the task prompt was social or non-social.

Procedure

We told participants that they would read and evaluate a short piece of writing from "another participant". In reality, we generated the writing using ChatGPT version 4o. We asked ChatGPT to generate a 300 word response to the prompt and to write convincingly like a real human. We then edited the text to appear more human-like by, for example, removing classic AI markers like dashes and concluding sentences and ensuring that the information was not too generic, such that the writing could reasonably be attributed to both a human and AI.

The prompt for the piece of writing varied between conditions:

- *Social conditions*: "Please write a description of a close family member or friend, explaining why they are special to you."

- *Non-social conditions*: "Please write a short description of a book, TV show, or film of your choice."

We explained that the "other participant" was asked several questions about how they produced their answer, including whether or not they used an AI tool like ChatGPT. We explained that the participant was encouraged to be honest and told that they would be paid regardless. The response from the "other participant" varied between conditions:

- *Control conditions*: "The participant reported that they did not use any AI tool like ChatGPT. Instead, they worked on the response themselves from start to finish."
- *Tool outsourcing conditions*: "The participant reported using ChatGPT to provide ideas, inspiration, and feedback. The participant told us that they edited and rewrote ChatGPT's suggestions and finished writing the response themselves."
- *Full outsourcing conditions*: "The participant reported using ChatGPT to complete the task. The participant told us that they copied ChatGPT's output word-for-word, rather than producing the response themselves."

Next, we presented participants with a randomly-chosen pre-generated essay answer to the prompt (see Supplementary Tables 2 and 3 for full essay answers). In the social conditions, the answer either referred to the participant's father, their sister, or their best friend. In the non-social conditions, the answer either referred to the book The Hobbit, the TV show Buffy the Vampire Slayer, or the film Titanic. Reading times and responses to a follow-up comprehension question suggested that participants read the essay answers in sufficient detail (see Supplementary Table 4).

Finally, we asked participants about their perceptions of the essay answer and the "other participant". We asked how well-written, meaningful, and authentic they thought the answer was (7-point Likert scales), what letter grade they would give the answer (A-E), and how much they would hypothetically reward the other participant for their work (from £0.00 to £1.00). We also asked how well each of the following words described the other participant: competent, warm, moral, lazy, and trustworthy (7-point Likert scales).

At the end of the study, we gave participants a manipulation check and asked them whether they believed the manipulation. Almost all participants correctly reported the condition that they were in and most participants stated that they believed the essay response was written in the way we described, suggesting that the manipulation was successful (see Supplementary Table 5). We also asked participants several questions about ChatGPT.

Pre-registration

We pre-registered the study on the Open Science Framework[1].

Statistical Analysis

We fitted two Bayesian multilevel models to the data. The first model was a multivariate cumulative-link ordinal model including all Likert scales as separate response variables. The second model was a zero-one-inflated-beta model applied specifically to the reward question, which was a slider scale varying between 0 and 1. For both models, we included fixed effects for the interaction between outsourcing type and task type and varying intercepts and slopes for essay answers. We used regularising priors for all parameters to impose conservatism on parameter estimates. All models converged normally ($\hat{R} \leq 1.01$).

Results

We first looked at character evaluations. We found that even when provided with concrete output, people were still perceived more negatively across all character evaluations if they outsourced the writing task to AI, either by using ChatGPT as a collaborative tool or by copying the text from ChatGPT verbatim (Supplementary Figure 5; Supplementary Table 6). In contrast to Study 1, however, we did not find any differences in character evaluations between the tool

[1] Due to a technical error with archiving this pre-registration on the Open Science Framework, the timestamp for the registration was lost. However, on our OSF project (https://osf.io/xhmzk), it is possible to view our pre-registration document file and its timestamped upload date.

outsourcing and full outsourcing conditions. We did not find differences in character evaluations between social and non-social tasks and did not find any interaction effects.

Turning to evaluations of the work itself, we found that the AI-outsourced work (either outsourced by using AI as a collaborative tool or fully outsourced) was judged as being equally well written to the work in the control condition (Figure 3; Table 2). This is in line with the writing indeed being identical in all conditions. Interestingly, however, we found that essay responses that were ostensibly generated using AI were perceived as less meaningful and less authentic compared to essay responses ostensibly written by a human. Participants also marked AI-generated essays with a lower grade and rewarded AI-generated essays with a lower hypothetical monetary bonus. In contrast to Study 1, we did not find differences in perceptions of the work between the tool outsourcing and full outsourcing conditions, except for the reward question, where fully outsourced essays (i.e., essays copied verbatim from ChatGPT) were rewarded £0.23 less than essays generated using AI as a collaborative tool. We did not find any differences between social and non-social tasks and did not find any interaction effects.

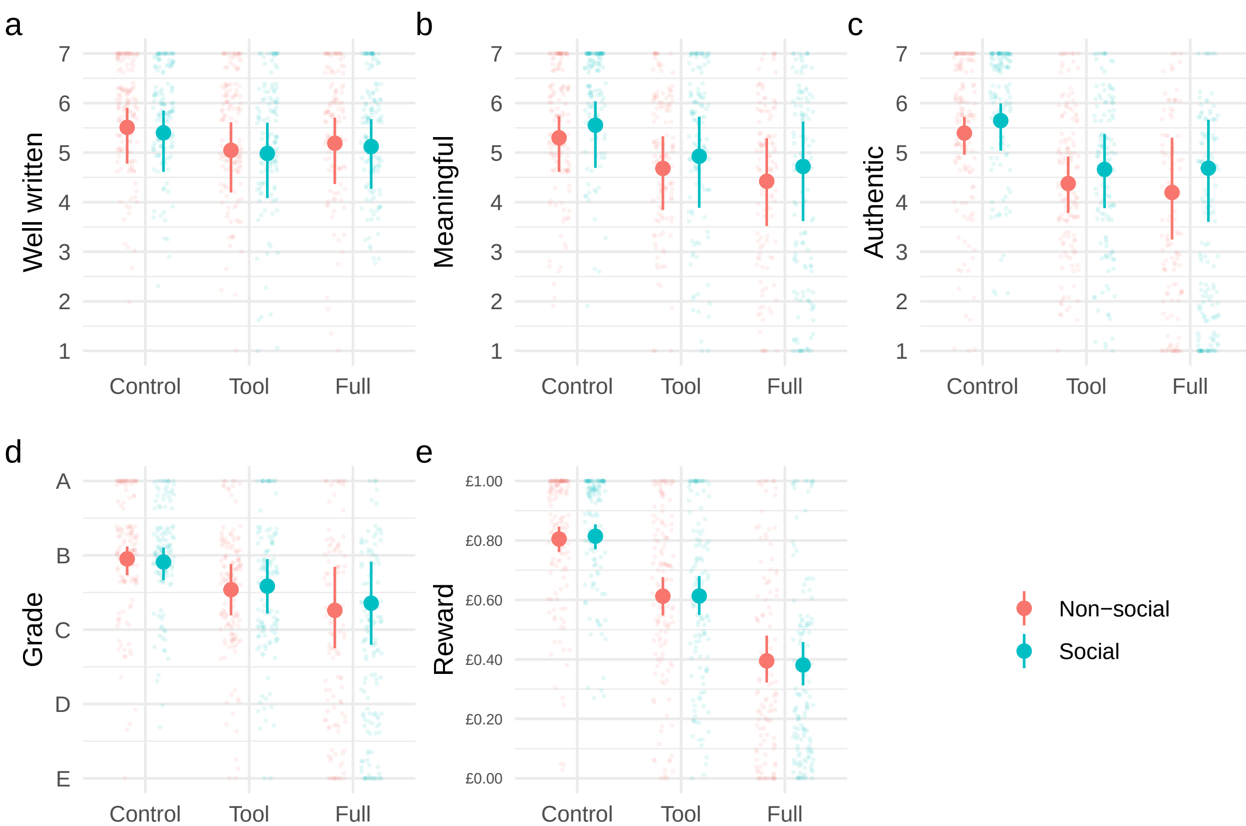
Discussion

In Study 2, we turned to look at how people perceived both the outsourcer and the outsourced work when given specific output in a social or non-social task that was described as being produced independently by a person, produced by a person in collaboration with AI as a tool, or outsourced in full to AI. We find that our results generalise from character judgments to perceptions of the work itself: text purportedly generated using AI was perceived to be less meaningful, less authentic, and less reward-worthy compared to the same text described as human-generated.

Surprisingly, we found no differences in the effect of AI-outsourcing between social and non-social tasks. This may be due to the particular tasks we chose. Writing *about* someone close to you is not quite the same as writing something *for* someone close to you, as is the case with wedding vows, love letters, and bereavement cards. We also found no differences between the tool and full outsourcing conditions, aside from the lower rewards given to participants in the latter

Figure 3

Perceptions of the Work in Study 2



Note. Participants in the control condition, the tool outsourcing condition, and the full outsourcing condition evaluated the essay response to the writing task. Participants rated whether the essay response was (a) well-written, (b) meaningful, and (c) authentic. Participants also (d) graded the work and (e) rewarded the work with a hypothetical monetary bonus. Jittered points represent participant responses to the questions, split by whether the writing task was a non-social task (red) or a social task (blue). Point ranges are estimated marginal means from the fitted model, pooling over essay answers. Points and line ranges represent posterior medians and 95% credible intervals, respectively.

Table 2

Pairwise Contrasts for Perceptions of the Work in Study 2

	Response				
	Well written	Meaningful	Authentic	Grade	Reward
Effect of outsourcing type					
Task type = Social					
Tool Social - Control Social	-0.42 [-0.84 0.03]	-0.64 [-1.11 -0.08]	-1.01 [-1.47 -0.35]	-0.33 [-0.60 -0.02]	-0.20 [-0.27 -0.13]
Full Social - Control Social	-0.28 [-0.63 0.09]	-0.84 [-1.55 -0.06]	-0.95 [-1.93 -0.07]	-0.55 [-1.07 -0.04]	-0.43 [-0.50 -0.36]
Full Social - Tool Social	0.14 [-0.39 0.67]	-0.21 [-1.13 0.74]	0.04 [-1.12 1.12]	-0.23 [-0.84 0.36]	-0.23 [-0.32 -0.14]
Task type = Non-social					
Tool Non-social - Control Non-social	-0.46 [-0.92 -0.02]	-0.62 [-1.09 -0.08]	-1.03 [-1.47 -0.49]	-0.42 [-0.71 -0.07]	-0.19 [-0.26 -0.12]
Full Non-social - Control Non-social	-0.32 [-0.70 0.03]	-0.90 [-1.56 -0.08]	-1.23 [-2.09 -0.12]	-0.71 [-1.16 -0.13]	-0.41 [-0.49 -0.32]
Full Non-social - Tool Non-social	0.14 [-0.39 0.71]	-0.28 [-1.06 0.62]	-0.21 [-1.19 0.97]	-0.29 [-0.86 0.34]	-0.22 [-0.31 -0.12]
Effect of task type					
Control Social - Control Non-social	-0.10 [-0.56 0.33]	0.28 [-0.36 0.73]	0.27 [-0.21 0.64]	-0.04 [-0.27 0.17]	0.01 [-0.05 0.06]
Tool Social - Tool Non-social	-0.06 [-0.67 0.56]	0.27 [-0.61 0.99]	0.29 [-0.41 0.95]	0.04 [-0.30 0.41]	0.00 [-0.09 0.09]
Full Social - Full Non-social	-0.07 [-0.64 0.51]	0.30 [-0.59 1.15]	0.48 [-0.37 1.38]	0.09 [-0.33 0.57]	-0.02 [-0.12 0.09]
Interaction effect					
Interaction: Tool - Control	0.05 [-0.39 0.51]	-0.02 [-0.52 0.56]	0.02 [-0.51 0.62]	0.09 [-0.22 0.39]	-0.01 [-0.10 0.08]
Interaction: Full - Control	0.04 [-0.34 0.46]	0.03 [-0.59 0.73]	0.23 [-0.50 1.02]	0.13 [-0.23 0.55]	-0.03 [-0.12 0.08]
Interaction: Full - Tool	0.00 [-0.58 0.55]	0.05 [-0.74 0.89]	0.21 [-0.66 1.12]	0.05 [-0.43 0.53]	-0.01 [-0.13 0.10]

Note. Numbers reflect differences in marginal means on either a 7-point Likert scale (well-written, meaningful, authentic), a 5-point ordinal grade scale (grade), or a 0-1 sliding scale (reward). Estimates are pooled over essay answers. The bottom rows represent the interactions between outsourcing type and task type. Main numbers are posterior medians, numbers in the square brackets are 95% credible intervals.

condition. It is possible that because the set-up described to participants was of another participant who was asked to produce work on Prolific and then admitted they used AI, participants saw any kind of AI use as violating an implicit contract between the survey requester and respondent and judged them negatively accordingly.

In Study 3, we turn to explore potential mechanisms driving our effects. We assume that effort may play a role, since perceived effort is often used as a signal of one's moral character

(Cubitt et al., 2011) and cooperative intent (Celniker et al., 2023). Study 2 also suggested a role of authenticity: in line with work on the psychological importance of authenticity (Newman, 2019), people who outsource to AI may be perceived as producing work that is less authentically their own, leading to negative evaluations. To explore these potential mechanisms, we experimentally manipulate (1) how much effort someone puts into the task and (2) whether they outsource the task to a standard LLM like ChatGPT or a personalised LLM trained specifically on their own prior writings (and so therefore producing work that is more authentically "theirs"). We expected negative perceptions of outsourcing to be mitigated when the person uses a personalised LLM and expends significant effort on formulating prompts for the AI.

Study 3

Methods

Participants

We used the same power estimate from Study 1 to determine our target sample size of n = 750 (150 participants in each of five conditions). We recruited a convenience sample of 802 participants from the United Kingdom through Prolific. After excluding participants who failed our pre-treatment attention check, we were left with a final sample of 753 participants (462 female; 278 male; 9 non-binary / third gender; 4 undisclosed gender; mean age = 44.29 years). 74% of these participants reported having used ChatGPT before (see Supplementary Figure 6).

Design

We used the same "control plus 2x2" between-subjects design as in Study 1. In the experimental conditions, we manipulated whether people in the scenarios used a standard or personalised AI model, and whether people put more or less effort into the task. This resulted in five conditions overall: (*i*) the control condition, (*ii*) the standard-low-effort condition, (*iii*) the standard-high-effort condition, (*iv*) the personalised-low-effort condition, and (*v*) the personalised-high-effort condition. Our authenticity manipulation was inspired by recent psychological work looking at the credit-blame asymmetry in AI use (Earp et al., 2024), showing that people receive more personal credit for their work when they use an AI model trained on their own prior writings.

Procedure

The procedure was mostly identical to Study 1 to allow us to explore effects across a range of tasks, but we updated the study preamble and the presentation of the scenarios. For participants in the personalised AI conditions, we expanded the study preamble to explain that personalised AI models were trained on people's own prior writings and "tailored to each specific person and their own thoughts, feelings, and values". Then in the scenarios, we told participants in the experimental conditions:

- *Standard AI conditions*: "In order to complete this task, [the person] uses the AI tool ChatGPT."
- *Personalised AI conditions*: "In order to complete this task, [the person] uses a personalised AI tool."

We then told participants:

- *Low effort conditions*: "[The person] quickly gives the AI a rushed prompt and uses its first output."
- *High effort conditions*: "[The person] carefully gives the AI several detailed prompts and, after multiple rounds of changes, uses its resulting output."

At the end of the study, we asked participants to choose which of these was more authentic and effortful, respectively. 94% of participants stated that the personalised AI was more authentic and 99% of participants stated that giving the AI several detailed prompts was more effortful. This suggests that even if participants might not have felt the output was meaningfully authentic in the way that mattered (see Discussion), our participants agreed that using a personalised AI was at least more authentic than using a generic one.

Pre-registration

We pre-registered the study on the Open Science Framework (https://osf.io/vaq7u).

Statistical Analysis

We fitted the same Bayesian multivariate multilevel cumulative-link ordinal models as in Studies 1 and 2. All models converged normally ($\hat{R} \leq 1.01$).

Results

We first looked across all the tasks. On average, we found that people who outsourced to AI in a low effort way were perceived as less competent, less moral, lazier, and less trustworthy than people who put more effort into their use of AI (Figure 4; Table 3). By contrast, we found that character evaluations did not differ between people who used a standard AI model rather than a personalised AI model. We also found no interaction effects between effort and the type of AI used.

Table 3

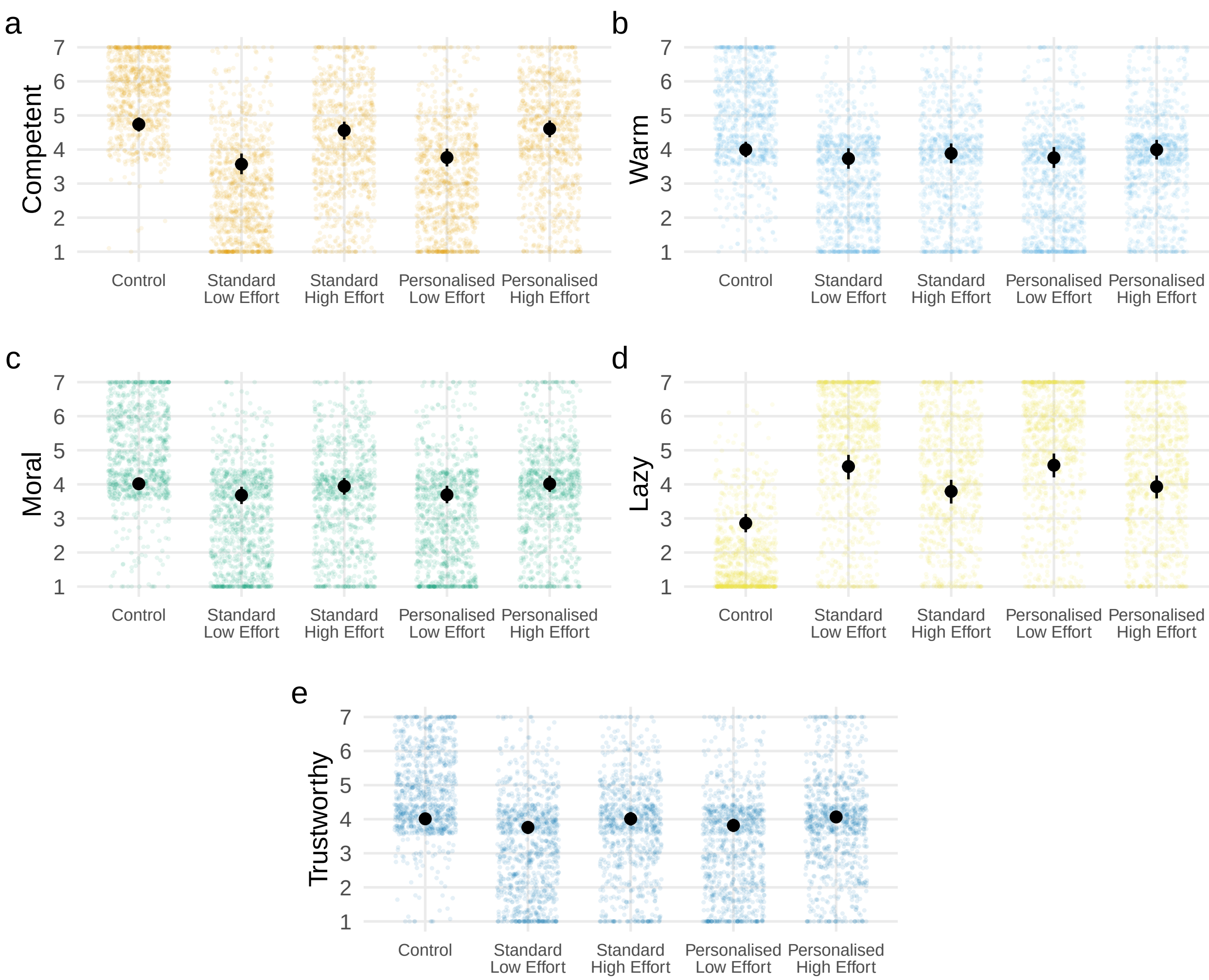
Overall Pairwise Contrasts in Study 3

	Response				
	Competent	Warm	Moral	Lazy	Trustworthy
Comparison to control					
Standard Low Effort - Control	-1.17 [-1.49 -0.85]	-0.26 [-0.53 0.00]	-0.34 [-0.58 -0.10]	1.67 [1.26 2.05]	-0.25 [-0.44 -0.06]
Standard High Effort - Control	-0.18 [-0.44 0.09]	-0.11 [-0.35 0.12]	-0.08 [-0.31 0.14]	0.94 [0.54 1.32]	0.00 [-0.19 0.19]
Personalised Low Effort - Control	-0.98 [-1.24 -0.70]	-0.24 [-0.50 0.02]	-0.33 [-0.56 -0.08]	1.71 [1.29 2.08]	-0.19 [-0.38 -0.01]
Personalised High Effort - Control	-0.13 [-0.38 0.13]	0.00 [-0.24 0.23]	0.00 [-0.22 0.23]	1.08 [0.69 1.44]	0.05 [-0.12 0.23]
Effect of AI type					
Standard Low Effort - Personalised Low Effort	-0.19 [-0.54 0.17]	-0.03 [-0.35 0.31]	-0.01 [-0.32 0.30]	-0.04 [-0.51 0.43]	-0.06 [-0.30 0.18]
Standard High Effort - Personalised High Effort	-0.04 [-0.36 0.27]	-0.11 [-0.41 0.20]	-0.07 [-0.36 0.22]	-0.14 [-0.61 0.34]	-0.05 [-0.28 0.17]
Effect of effort					
Standard Low Effort - Standard High Effort	-1.00 [-1.34 -0.62]	-0.15 [-0.47 0.17]	-0.26 [-0.56 0.04]	0.73 [0.25 1.21]	-0.25 [-0.50 -0.02]
Personalised Low Effort - Personalised High Effort	-0.84 [-1.16 -0.53]	-0.24 [-0.56 0.10]	-0.33 [-0.63 -0.03]	0.63 [0.15 1.08]	-0.25 [-0.48 -0.03]
Interaction effect					
Interaction effect	-0.15 [-0.61 0.32]	0.09 [-0.36 0.53]	0.06 [-0.36 0.49]	0.10 [-0.55 0.76]	0.00 [-0.32 0.32]

Note. Numbers reflect differences in marginal means on a 7-point Likert scale, pooling over participants and tasks. The bottom row represents the interaction between AI type and effort (i.e., the difference between the differences in the rows above). Main numbers are posterior medians, numbers in the square brackets are 95% credible intervals.

Figure 4

Overall Character Evaluations in Study 3

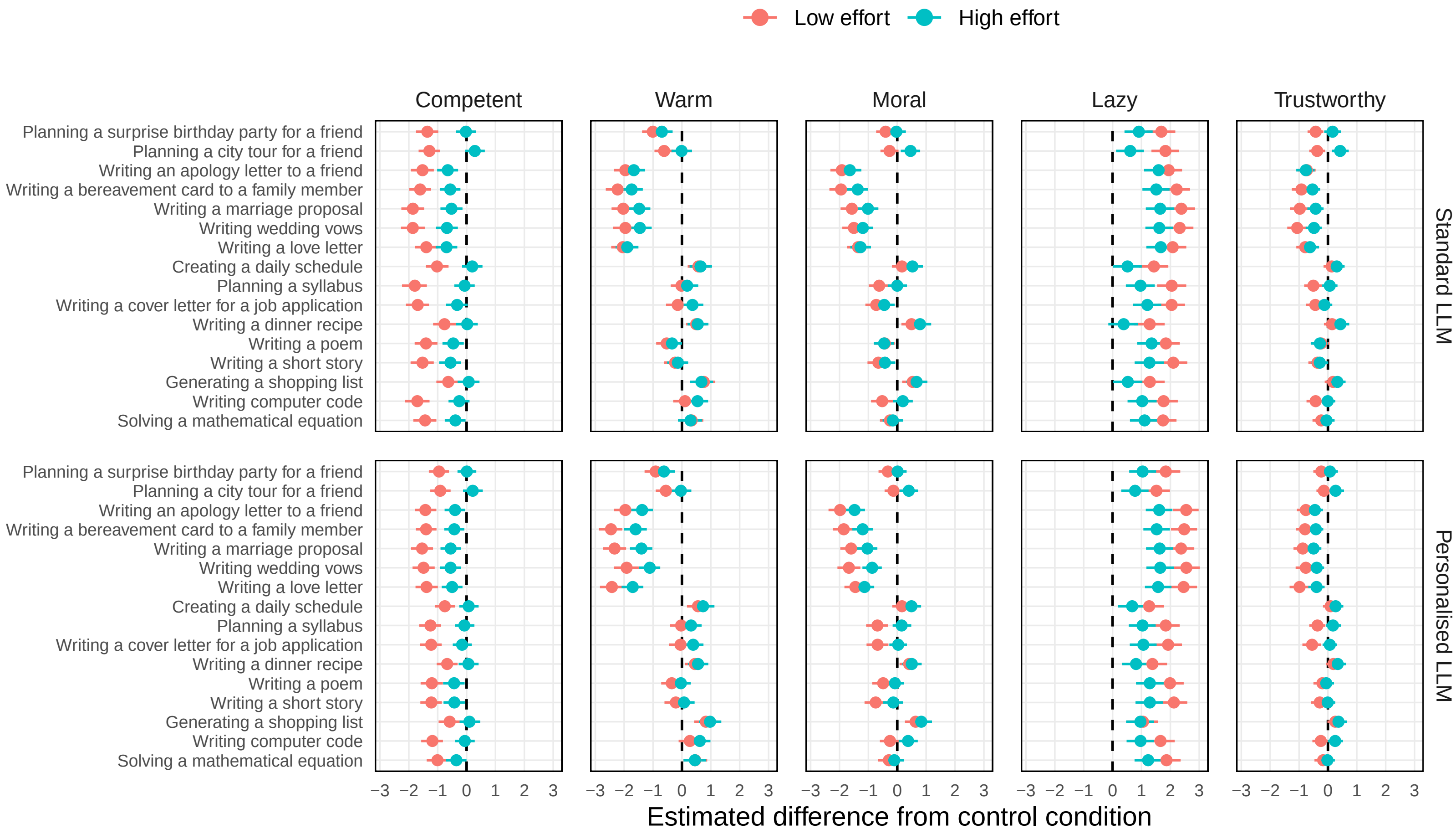


Note. Participants in the control condition and four AI outsourcing conditions evaluated people in the scenarios on (a) competence, (b) warmth, (c) morality, (d) laziness, and (e) trustworthiness. Coloured points represent participant responses to the questions, jittered for easier viewing. Black points are estimated marginal means from the fitted model, pooling over participants and tasks. Black points and line ranges represent posterior medians and 95% credible intervals, respectively.

As in Study 1, the effects of outsourcing to AI varied across the different tasks, especially for perceptions of warmth and morality (Figure 5). We again found that the negative causal effects of outsourcing to AI were particularly strong for tasks that are social, require social skills, impact others, have important consequences, and require effort (Supplementary Figures 7 and 8). Indeed, for tasks like writing wedding vows or writing a love letter, outsourcing to a personalised AI in a high effort way was still perceived more negatively than the control condition for all five character dimensions.

Figure 5

Variation in the Effects of Outsourcing across Tasks in Study 3



Note. Tasks are ordered from most social (top) to least social (bottom) according to ratings from a pilot study. Point ranges are differences in marginal means on a 7-point Likert scale for the low effort conditions (red) and high effort conditions (blue) compared to the control condition. Upper panels refer to the standard LLM conditions, and lower panels refer to the personalised LLM conditions. Points and ranges represent posterior medians and 95% credible intervals, respectively.

Discussion

In Study 3, we found that effort is an important mechanism by which outsourcing to AI leads to negative character evaluations. People who engaged in effortless copying of the AI's first output were perceived more negatively than people who spent time and effort crafting the AI's output with multiple prompts. Nevertheless, for social tasks like writing wedding vows or love letters, outsourcing to AI in a high effort way was still perceived more negatively than completing the task oneself.

Interestingly, we found no effect of authenticity as proxied by the use of a personalised AI that is trained on one's own prior writings compared to a standard AI like ChatGPT. This could indicate that authenticity is not an important mechanism underlying the effect of outsourcing on negative character evaluations. However, our specific manipulation may not have moved the needle on authenticity enough to impact character evaluations. While previous work has found an effect of personalised AI models on perceived credit (Earp et al., 2024), and the majority of participants in our study stated that the personalised AI was more authentic than a standard model like ChatGPT, it is possible that perceptions of *meaningful* authenticity in our study remained low even with the personalised AI model. An AI could be perfectly trained on all apologies that a person has ever written, but one might still think that a specific apology it then generates in a new instance is not an *authentic* apology. Therefore, even if people were described as outsourcing to an AI that was trained on their own writing and therefore personalised, participants still may not have seen the specific output as being meaningfully authentic in the way that matters for character judgments.

In Study 4, we turn to look at a third potential mechanism: a perceived lack of importance attached to the task. When participants read about someone who outsources to AI in our studies, they may be inferring that they simply did not care enough about the task – "If this was important to them, they would do it themselves!". To the extent that we especially want people to care about their relationships with others – the kind of things demonstrated through love letters, apology notes, and gift-giving – this could explain the particular negativity we see for social tasks compared to tasks like writing daily schedules, recipes, or computer code. To test this, in Study 4, we attempted to counteract inferences about care for the task by explicitly telling participants that someone had a good reason for using AI: that they really cared about the task and used AI because they wanted to get it right.

Study 4

Methods

Participants

We used the same power estimate from Study 1 to determine our target sample size of n = 750 (150 participants in each of five conditions). We recruited a convenience sample of 800 participants from the United Kingdom through Prolific. After excluding participants who failed our pre-treatment attention check, we were left with a final sample of 758 participants (398 female; 346 male; 8 non-binary / third gender; 6 undisclosed gender; mean age = 41.72 years). 80% of these participants reported having used ChatGPT before (see Supplementary Figure 9).

Design

We used the same "control plus 2x2" between-subjects design as in Studies 1 and 3. In the experimental conditions, we manipulated whether people in the scenarios used AI as a tool or "fully" outsourced to AI, and whether people had bad or good reasons for using AI. This resulted in five conditions overall: (*i*) the control condition, (*ii*) the tool-bad-reason condition, (*iii*) the tool-good-reason condition, (*iv*) the full-bad-reason condition, and (*v*) the full-good-reason condition.

Procedure

The procedure was mostly identical to Study 3, with two changes. First, we reduced the number of tasks, focusing on eight tasks (four "social" tasks and four "non-social" tasks) that fit with the manipulation of the updated design (since, for example, participants might find it difficult to see how someone could deeply value a shopping list and want to get it right). Second, we updated the presentation of the scenarios. We told participants in the experimental conditions:

- *Bad reason conditions*: "Because they are really short on time and want to complete the task quickly, [the person] uses the AI tool ChatGPT."
- *Good reason conditions*: "Because this task is really important to them and they want to make sure they get it right, [the person] uses the AI tool ChatGPT."

We then told participants:

- *Tool outsourcing conditions*: "[The person] asks ChatGPT to provide ideas, inspiration, and feedback, but they edit and rewrite the suggestions and finish the task themselves."
- *Full outsourcing conditions*: "[The person] copies ChatGPT's output word-for-word, rather than doing it themselves."

In addition to the five character evaluations, on each page we also asked participants, on a 7-point Likert scale, how much they thought the person cared about the task.

Pre-registration

We pre-registered the study on the Open Science Framework (https://osf.io/vaq7u).

Statistical Analysis

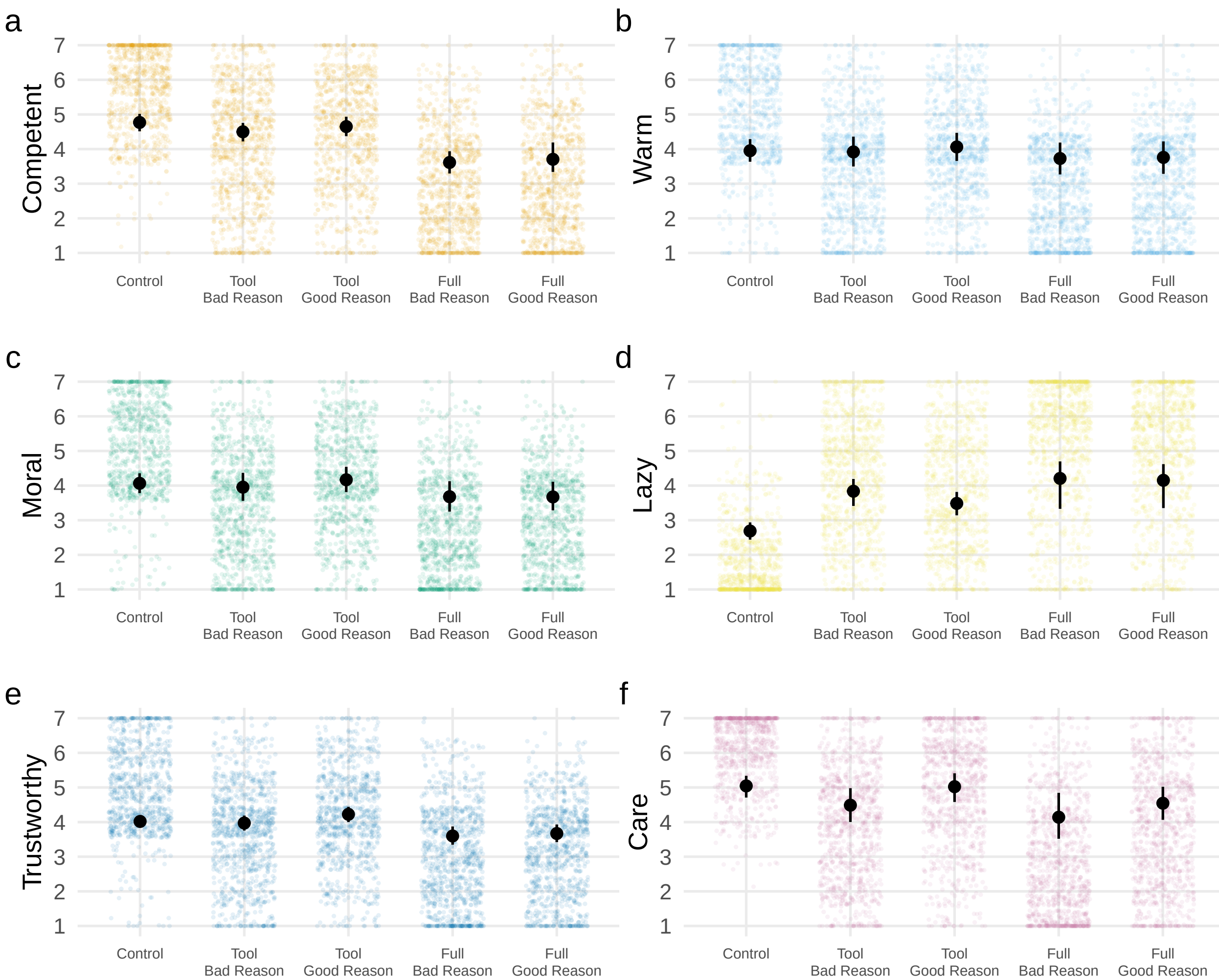
We fitted the same Bayesian multivariate multilevel cumulative-link ordinal models as in Studies 1 and 3. All models converged normally ($\hat{R} \leq 1.01$).

Results

We first looked across all the tasks. In line with our previous results, we found that people who fully outsourced to AI by copying the output verbatim were perceived as less competent, less moral, and less trustworthy than people who used AI as a collaborative tool (Figure 6; Table 4). Perhaps surprisingly, though, people's reasons for outsourcing to AI did not appear to influence character evaluations when pooling across all the tasks. When looking at the tasks overall, character evaluations did not differ between people who really cared about the task and wanted to get it right and people who used AI because they were short on time and wanted to complete the task quickly. This was true both when using the AI as a tool or outsourcing in full.

Figure 6

Overall Character Evaluations in Study 4



Note. Participants in the control condition and four AI outsourcing conditions evaluated people in the scenarios on (a) competence, (b) warmth, (c) morality, (d) laziness, and (e) trustworthiness. Coloured points represent participant responses to the questions, jittered for easier viewing. Black points are estimated marginal means from the fitted model, pooling over participants and tasks. Black points and line ranges represent posterior medians and 95% credible intervals, respectively.

Table 4

Overall Pairwise Contrasts in Study 4

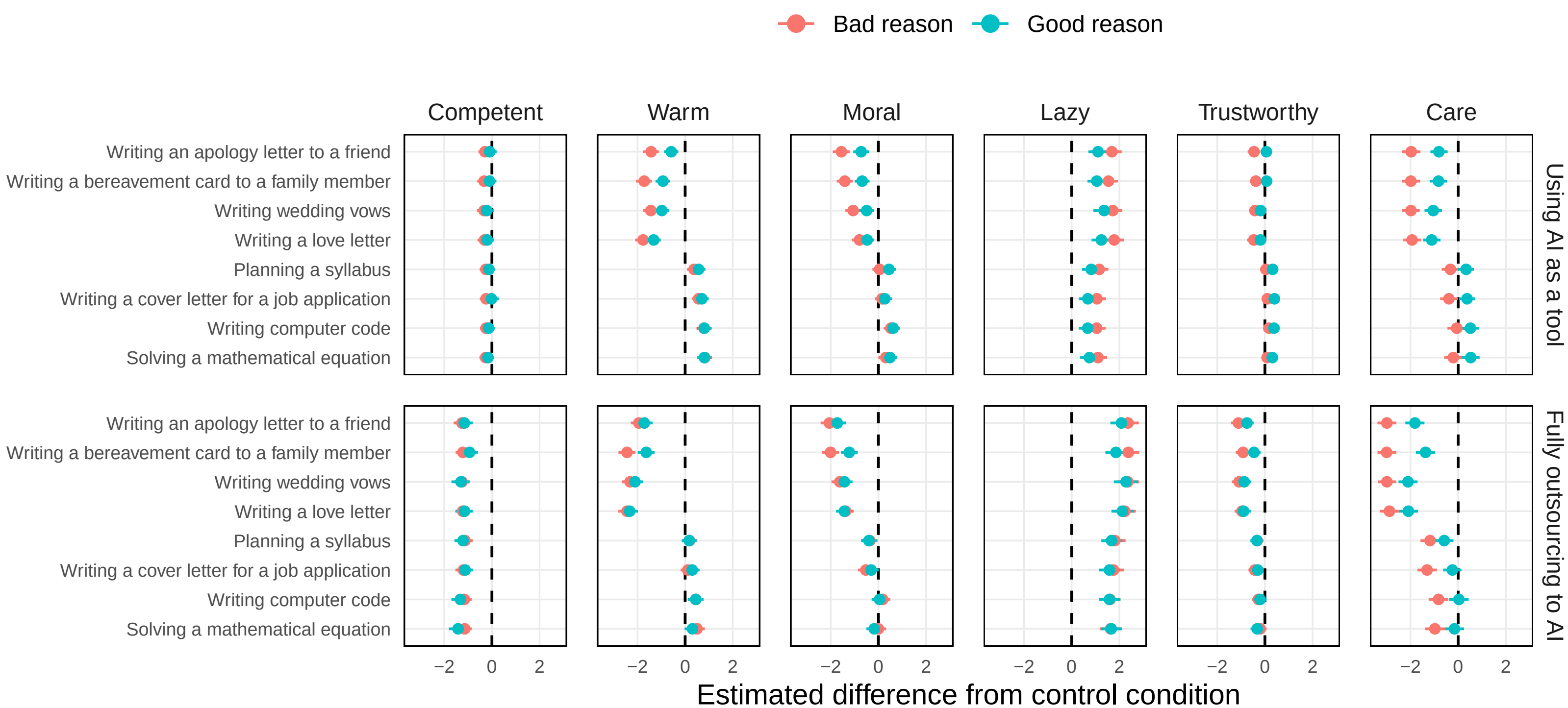
	Response					
	Competent	Warm	Moral	Lazy	Trustworthy	Care
Comparison to control						
Tool Bad Reason - Control	-0.27 [-0.53 -0.02]	-0.03 [-0.37 0.30]	-0.11 [-0.45 0.24]	1.16 [0.73 1.51]	-0.05 [-0.27 0.16]	-0.56 [-0.97 -0.11]
Tool Good Reason - Control	-0.12 [-0.38 0.13]	0.11 [-0.21 0.43]	0.11 [-0.19 0.39]	0.80 [0.43 1.17]	0.21 [-0.02 0.42]	-0.02 [-0.37 0.31]
Full Bad Reason - Control	-1.16 [-1.45 -0.83]	-0.22 [-0.59 0.14]	-0.39 [-0.75 0.00]	1.58 [0.75 2.01]	-0.42 [-0.68 -0.15]	-0.92 [-1.46 -0.29]
Full Good Reason - Control	-1.08 [-1.40 -0.62]	-0.19 [-0.54 0.16]	-0.40 [-0.73 -0.05]	1.50 [0.78 1.94]	-0.35 [-0.59 -0.09]	-0.50 [-0.91 -0.07]
Effect of outsourcing type						
Full Bad Reason - Tool Bad Reason	-0.89 [-1.19 -0.55]	-0.19 [-0.66 0.27]	-0.27 [-0.77 0.21]	0.42 [-0.53 0.98]	-0.37 [-0.68 -0.05]	-0.36 [-1.04 0.39]
Full Good Reason - Tool Good Reason	-0.96 [-1.32 -0.46]	-0.30 [-0.78 0.16]	-0.50 [-0.93 -0.04]	0.70 [-0.11 1.24]	-0.56 [-0.85 -0.23]	-0.48 [-0.99 0.07]
Effect of reasons for outsourcing						
Tool Bad Reason - Tool Good Reason	-0.15 [-0.44 0.14]	-0.14 [-0.59 0.28]	-0.22 [-0.63 0.23]	0.36 [-0.16 0.82]	-0.25 [-0.53 0.03]	-0.54 [-1.04 0.01]
Full Bad Reason - Full Good Reason	-0.07 [-0.60 0.31]	-0.03 [-0.54 0.45]	0.01 [-0.48 0.49]	0.08 [-0.85 0.85]	-0.07 [-0.41 0.26]	-0.42 [-1.10 0.34]
Interaction effect						
Interaction effect	0.07 [-0.50 0.55]	0.11 [-0.57 0.75]	0.22 [-0.41 0.86]	-0.28 [-1.28 0.64]	0.18 [-0.26 0.61]	0.13 [-0.73 1.01]

Note. Numbers reflect differences in marginal means on a 7-point Likert scale, pooling over participants and tasks. The bottom row represents the interaction between outsourcing type and the reasons for outsourcing (i.e., the difference between the differences in the rows above). Main numbers are posterior medians, numbers in the square brackets are 95% credible intervals.

Importantly, though, as in our previous studies, the type of task mattered (Figure 7). Perceptions of outsourcing were particularly negative for tasks that are social, require social skills, impact others, have important consequences, and require effort (Supplementary Figures 10 and 11). Indeed, for socio-relational tasks like writing an apology letter and writing wedding vows, people using AI as a tool for good reasons were still perceived more negatively than the control condition on the dimensions of warmth, morality, laziness, and care, though not on the dimensions of competence or trustworthiness.

Figure 7

Variation in the Effects of Outsourcing across Tasks in Study 4



Note. Tasks are ordered from most social (top) to least social (bottom) according to ratings from a pilot study. Point ranges are differences in marginal means on a 7-point Likert scale for the bad reason conditions (red) and good reason conditions (blue) compared to the control condition. Upper panels refer to the tool outsourcing conditions, and lower panels refer to the full outsourcing conditions. Points and ranges represent posterior medians and 95% credible intervals, respectively.

Moreover, when we delved further into the task-specific estimates, we found that the reasons manipulation did indeed have an effect on character evaluations for social tasks – but not non-social tasks (Supplementary Figure 12). When writing a bereavement card, for example, people were perceived as less warm, less moral, lazier, and less trustworthy when they used AI to save time compared to when they used it because they cared about doing the task well. The same was not true for non-social tasks like writing computer code or solving a mathematical equation.

Discussion

In Study 4, we attempted to counteract the potential perception that outsourcing to AI reflects caring less about the task by explicitly informing participants about the person's reason for outsourcing: they outsourced to AI because they really cared about the task and wanted to get it right. As well as replicating our finding that fully outsourcing to AI is perceived more negatively than using AI as a tool, we also found an important effect of the reasons for outsourcing, but only for socio-relational tasks. When writing a bereavement card or an apology letter, for example, people were perceived more negatively if they used an AI tool to produce a quick output in a rush, rather than to ensure they got it right. Nonetheless, for socio-relational tasks, the "best" use of AI in this study – using AI as a tool because they cared about the task and wanted to get it right — *still* led to targets being perceived more negatively than if they had completed the task themselves.

While we have so far shown varying evidence for three different mechanisms that might underlie the negative perceptions of outsourcing to AI – effort, authenticity, and caring about the task – it is likely that these mechanisms are related. For example, outsourcing to AI might indicate a lack of effort, which then might signal a lack of authenticity and reduced care in the task, leading to negative character evaluations. Our previous studies have been unable to test causal models like these as we manipulated the mechanisms separately and independently. In Study 5, therefore, we bring all three mechanisms together and test their combined associations with character evaluations. To do this, we focus on a single socio-relational task — writing a love letter — which we elaborate for participants with a more detailed vignette.

Study 5

Methods

Participants

We conducted a power simulation to determine our target sample size. The simulation suggested that a sample size of 200 participants per condition (overall n = 600 for three conditions) would be required to detect a small-to-medium difference between conditions (Cohen's $d \approx 0.30$) with above 80% power.

We recruited a convenience sample of 651 participants from the United Kingdom through Prolific. After excluding participants who failed our pre-treatment attention check, we were left with a final sample of 610 participants (371 female; 233 male; 4 non-binary / third gender; 2 undisclosed gender; mean age = 42.85 years). 82% of these participants reported having used AI tools like ChatGPT before (see Supplementary Figure 13).

Design

We randomly allocated participants into one of three conditions in a between-subjects design: (*i*) the control condition, (*ii*) the tool outsourcing condition, or (*iii*) the full outsourcing condition. These conditions determined how the scenario was presented to participants.

Procedure

We presented participants with a vignette about a person, Adam, who is writing a love letter in a Valentine's Day card to his partner (see Supplementary Materials for full vignette wording). We told participants in each of the conditions:

- *Control condition*: "Adam decides to write the love letter in the card by himself."
- *Tool outsourcing condition*: "Adam decides to use AI to help write the love letter in the card. He asks ChatGPT to provide ideas, inspiration, and feedback, but he edits and rewrites the suggestions and finishes writing the love letter himself."
- *Full outsourcing condition*: "Adam decides to use AI to write the love letter in the card. He asks ChatGPT to write the love letter and copies the output word-for-word, rather than

writing it himself."

We then presented participants with the love letter that Adam wrote (in reality, this was written by ChatGPT version 4o; see Supplementary Materials for wording). On the following page, we asked participants what Adam wrote and whether he used AI to help. 95% of participants answered both of these comprehension questions correctly.

Using 7-point Likert scales, we then asked participants how much effort they thought Adam put into the love letter, how authentic they thought the love letter was, how much they thought Adam cared about the love letter, and the same five character evaluations as in our previous studies. In additional free response questions, we asked participants to explain how they felt towards Adam and how they would feel if they were Adam's partner. Finally, we asked participants several questions about AI tools like ChatGPT.

Pre-registration

We pre-registered the study on the Open Science Framework (https://osf.io/k9v7z).

Statistical Analysis

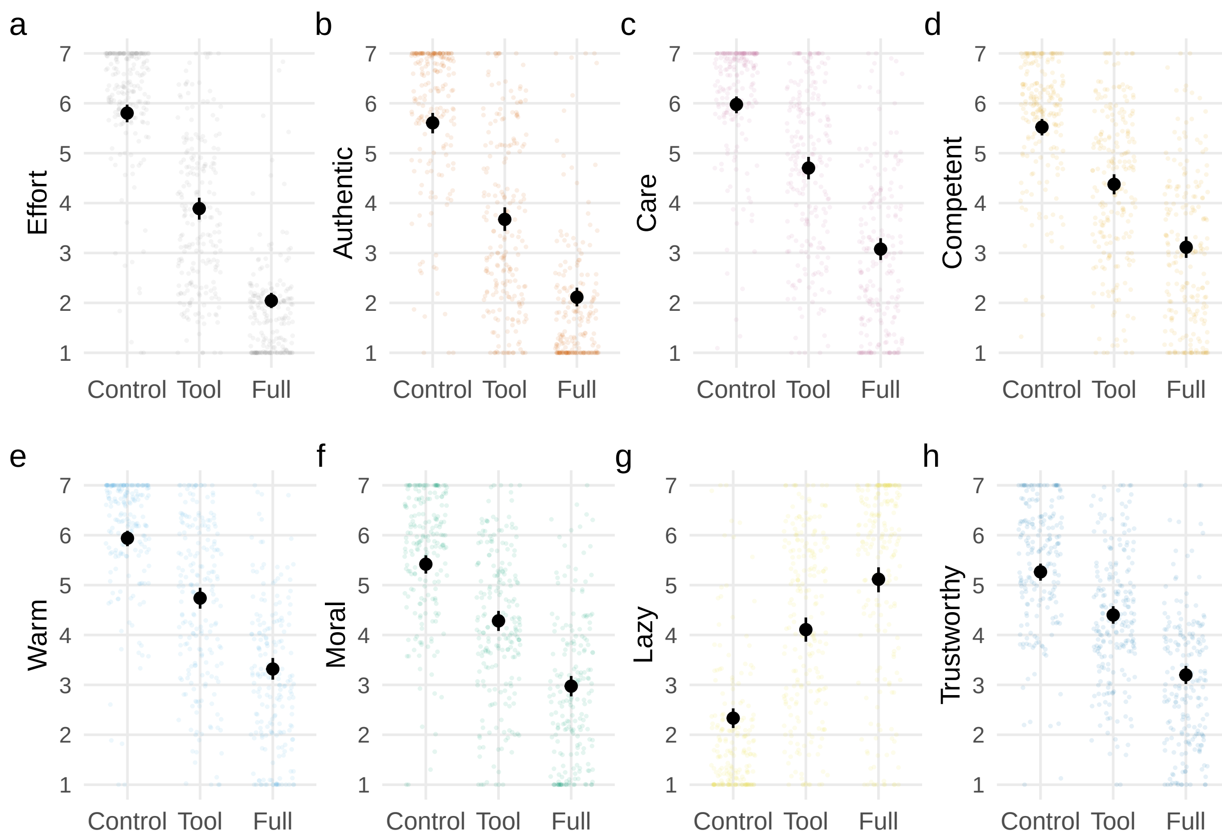
We fitted two Bayesian regression models to the data. The first model was a multivariate cumulative-link ordinal model including all Likert scales as separate response variables. The second model was a path model capturing the effect of outsourcing on character evaluations, both directly and indirectly through perceptions of effort, authenticity, and care. In this second model, we included ordinal predictors as monotonic effects and modelled the five character evaluations as a single latent variable. We used regularising priors for all parameters to impose conservatism on parameter estimates. All models converged normally ($\hat{R} \leq 1.01$).

Results

Across all measures, we found that outsourcing the love letter to AI was perceived more negatively compared to the control condition and that fully outsourcing to AI was perceived more negatively than using AI as a collaborative tool (Figure 8; Table 5). Not only did outsourcing the love letter lead to more negative character evaluations, but outsourcing to AI was also seen as less effortful, less authentic, and indicative of caring less about the task.

Figure 8

Perceptions of the Person and the Love Letter in Study 5



Note. Participants in the control, tool outsourcing, and full outsourcing conditions rated (a) the amount of effort put into the love letter, (b) how authentic the love letter was, (c) how much the person cared about the love letter, and (d-h) five character evaluation measures. Coloured points represent participant responses to the questions, jittered for easier viewing. Black points are estimated marginal means from the fitted model. Black points and line ranges represent posterior medians and 95% credible intervals, respectively.

Table 5

Pairwise Contrasts in Study 5

	Response							
	Effort	Authentic	Care	Competent	Warm	Moral	Lazy	Trustworthy
Tool - Control	-1.91 [-2.18 -1.64]	-1.94 [-2.23 -1.61]	-1.27 [-1.54 -1.00]	-1.15 [-1.40 -0.89]	-1.20 [-1.45 -0.95]	-1.14 [-1.39 -0.88]	1.77 [1.47 2.07]	-0.86 [-1.11 -0.62]
Full - Control	-3.76 [-3.98 -3.52]	-3.50 [-3.77 -3.22]	-2.90 [-3.16 -2.63]	-2.41 [-2.67 -2.14]	-2.62 [-2.88 -2.37]	-2.44 [-2.71 -2.17]	2.78 [2.47 3.09]	-2.07 [-2.30 -1.82]
Full - Tool	-1.85 [-2.11 -1.58]	-1.56 [-1.87 -1.26]	-1.63 [-1.93 -1.31]	-1.26 [-1.55 -0.97]	-1.42 [-1.72 -1.12]	-1.31 [-1.60 -1.02]	1.01 [0.65 1.35]	-1.20 [-1.45 -0.95]

Note. Numbers reflect differences in marginal means on a 7-point Likert scale. Main numbers are posterior medians, numbers in the square brackets are 95% credible intervals.

Exploratory text analysis of participants' free responses supported this quantitative pattern (see Supplementary Materials for methodology and Supplementary Table 7 for results). When comparing word frequencies between conditions, we found that Adam was more likely to be described as "lazy" and less likely to be described as "caring", "thoughtful", and "genuine" in both outsourcing conditions compared to the control condition. Adam was also more likely to be described as "romantic" and as someone who "loves" his partner when he used AI as a collaborative tool, compared to when he fully outsourced the love letter to AI.

When we included all the variables in a single path model, we found that outsourcing influenced character evaluations both directly and indirectly through our proposed mechanisms (Figure 9). The indirect effects showed that people perceived outsourced work as less effortful, and less effortful work was seen as less authentic and indicating less care about the task. In turn, less authenticity and care were associated with more negative evaluations of the person. Effort itself was not directly related to character evaluations, suggesting that effort works solely through perceptions of authenticity and care.

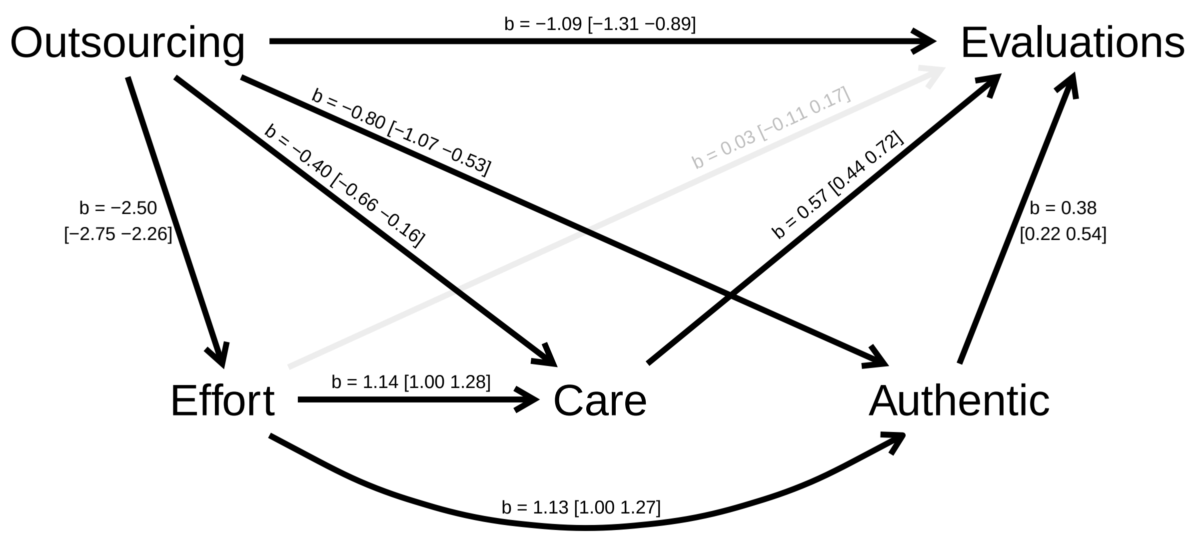
General Discussion

The release of openly available generative AI LLMs has changed lives, promising to let people do more tasks, more efficiently, and perhaps to do so better than they could alone. People can — and *do* — use AI tools like ChatGPT to, for example, create dinner recipes, assist with coding, and even write job applications (Department for Science, Innovation & Technology, 2024). But it is not only such routine, everyday, and non-social tasks that AI now "assists" with. People can use AI for a seemingly endless range of social tasks too, from crafting apology letters to writing condolences to even writing wedding vows. In this paper, across five pre-registered experiments, we show how — and why — AI-outsourcing shapes perceptions of others in a world where outsourcing has never been easier and cheaper.

In Study 1, we showed that people who outsourced tasks to AI were perceived more negatively than people who completed the tasks by themselves. These negative impressions were particularly strong for people who used AI to complete socio-relational tasks, such as writing a

Figure 9

Path Model in Study 5



Note. All predictors were modelled as monotonic effects, such that parameters can be interpreted as the expected average difference between two adjacent categories of the ordinal predictor on the logit scale. The "evaluations" outcome variable was modelled as a single latent variable with loadings from all five character evaluations (competence, warmth, morality, laziness, and trustworthiness).

love letter or writing wedding vows, and for people who copied the model's first output verbatim without acknowledging their reliance on AI. Moreover, these negative perceptions were found even for the "best case" of openly acknowledging the use of AI as a collaborative tool. In Study 2, we showed that people perceive both the outsourcer and the outsworked work more negatively, with outsourced work perceived as less meaningful, less authentic, and less reward-worthy than ostensibly human-generated writing. In Study 3, we showed that while it matters whether people spent time crafting the AI prompts or simply gave a rushed initial prompt, even expending effort into crafting the best prompts was still not enough to counteract the negative effects from using

AI. In Study 4, we explored the potential role of inferred importance and found that while explicitly telling participants that the person used AI because they cared about the task reduced negative perceptions for social tasks, it was still not enough to eliminate negative perceptions completely. In Study 5, we showed that a perceived lack of effort is taken to signal both a lack of authenticity and lack of importance attached to the task, and these independently influenced character judgments above and beyond the effect of effort.

Our findings extend work on the moralisation of effort. Studies have shown that people inherently value effort and perceive displays of effort as costly signals of one's moral character and cooperative intent (Celniker et al., 2023). And yet it has remained unclear how we might view others who outsource to AI; how these effects might vary based on how socio-relational the task is; how different ways of outsourcing influence perceptions; how outsourcing has different effects on different kinds of social perceptions; and why exactly effort has the effects that it does. Across our studies, we provide new insight into all of these questions. In line with previous work on the importance of effort, we show that people negatively judge those who outsource to AI. We show that the type of task does matter, whereby outsourcing to AI for socio-relational tasks leads to particularly negative perceptions. We show that different ways of outsourcing lead to differences in the degree of negative perceptions but that, critically, even outsourcing to AI in the "best" way (e.g., using it as a tool and finishing the work oneself while being honest about the AI use) is still not enough to eliminate the negative consequences. We show that negative perceptions from outsourcing tended to go together, even if outsourcing on social tasks led to particularly negative effects on warmth and morality traits. And finally, we provide further insight into why effort matters. The reduced effort from outsourcing socio-relational tasks to AI signals that the work is less authentically one's own and that the person cares less about the task (and therefore, perhaps, the relationship). The lack of a direct effect of perceived effort in our path model showed that it is inferences of authenticity and care, rather than perceived effort per se, that are associated with negative character evaluations. As a participant in our final study put it: "*If he really cared, he would have just done it by himself from scratch*" (female, 25 years old).

Our findings cohere with the philosophical idea that there is value in *how* a task was done, and not merely *whether* it was done (Goodman, 2010; Stohr, 2006). For many socio-relational tasks, it might seem that part of the constitutive action is the *process* by which it occurs: an apology that does not contain a genuine reflection and commitment to do better, rather than just the words "I am sorry", might not seem to be an apology at all. In contrast, for many of the non-social tasks, it is easier to distinguish the importance of the process from the outcome. In this way, our work suggests that people rarely adopt a purely utilitarian perspective in which outcomes are the sole determinant (Everett & Kahane, 2020; Kahane et al., 2018). Instead, their judgments cohere more with ideas from virtue ethics about the importance of *doing* (Stohr, 2006). Outsourcing to AI – especially for social tasks — may allow us to produce similar outputs, but by severing the outcome from the practice of doing, it may risk the development and maintenance of our human virtues (Vallor, 2015).

AI is often being marketed as being able to help us to do more and more tasks, promising gains of efficiency that align with societal incentives for "hacks" that encourage people to do more-and-more with less energy and effort. Our work, however, highlights that when it comes to our psychology, efficiency is not the only currency. Instead, *in*efficiency can sometimes pay off more, especially for social tasks. By expending effort themselves instead of outsourcing to AI, people are able to signal authenticity and care for the task, and this can lead to better reputations (see also Celniker et al., 2023). Correspondingly, expending effort, even "unnecessarily", is not as irrational, biased, or suboptimal as we might think from a utilitarian perspective in which outcomes are the only things that matter. Instead, it is precisely this inefficiency that helps people signal things that they care about and connect with others, thereby arguably reflecting a deeply rational reflection of virtues and the importance of social ties (Everett et al., 2016).

Most speculatively, our results on the negative effects of AI-outsourcing on character judgments highlight potential risks in how increased use of AI could lead to negative consequences for social ties, especially if people start to assume, by default, that others are using AI for the kind of tasks that matter. Sociologists have highlighted concerns about the negative effects that outsourcing to AI can have on our "connective labour", arguing that while AI can enhance certain tasks, it cannot replicate the depth of human relationships essential for effective caregiving, education, and support (Pugh, 2024). Similar arguments have been made about the risks of outsourcing empathy to AI (Landes & Everett, 2025). In this way, the rapid move towards using AI for more and more tasks could have serious and unintended consequences on the way we connect with one another, serving to further weaken the social ties that bind us into a community.

Limitations and Directions for Future Research

The studies in this paper are not without their limitations. While we included a range of different socio-relational and professional tasks in an effort to improve the generalisability of our findings across domains, it would be interesting for future work to additionally explore the generalisability and variability of our findings across countries with different AI infrastructures and readiness levels (Oxford Insights, 2024; Tortoise Media, 2024) and over time as AI use becomes more commonplace. By focusing on generalisability across various real-world tasks in which people outsource, it could also be argued that our design lacks the richness of information in extended vignettes that might influence character evaluations. While we have advanced previous research in highlighting the ways in which effort influences perceptions of authenticity and care, it will be interesting for future research to delve deeper into these mechanisms, both philosophically and psychologically: *why* is it that the perceived care for the task matters, and what are the boundary conditions of these effects? Finally, while we have demonstrated negative perceptions of outsourcing in this paper, it will be important for future research to explore when people might deem outsourcing to AI as acceptable or even preferable. Several of the participants in our final study expressed in their free responses that they would have been okay with Adam using AI to write the love letter if he was not a confident writer or had a learning difficulty that made writing challenging, such as dyslexia. In line with this, some research has found that people are more accepting of cognition-enhancing technologies and drugs when they are used to repair cognitive functions, rather than to enhance cognitive functions beyond "normal" levels (Medaglia et al., 2019; Rudski, 2014). Future research should explore whether negative perceptions of outsourcing persist when AI is used in a reparative way.

Conclusions

To conclude, across five pre-registered studies, we have demonstrated negative perceptions of outsourcing to AI. Our participants perceived individuals who outsource tasks to AI more negatively across a range of character dimensions and perceived outsourced work as less meaningful and authentic. Negative perceptions were particularly strong for socio-relational tasks, such as writing wedding vows, and were compounded when the outsourcer copied the AI's output verbatim and did not honestly acknowledge their use of AI. These findings connect with broader debates about the importance of *doing* in social relationships, and highlight that for many tasks – especially those that are more socio-relational – it might be better to move away from a focus on making things more efficient at all costs and instead bring back a recognition of the power of *in*efficiency. Doing something oneself, even if AI could do it quicker and easier, signals one that is authentic and cares about the task and therefore can help bind us together. In a world of algorithm-mediated interactions, AI is no substitute for investing effort into our interpersonal relationships.

References

Abele, A. E., Ellemers, N., Fiske, S. T., Koch, A., & Yzerbyt, V. (2021). Navigating the social world: Toward an integrated framework for evaluating self, individuals, and groups. *Psychological Review*, *128*(2), 290–314. https://doi.org/10.1037/rev0000262

Allaire, J. J., Teague, C., Scheidegger, C., Xie, Y., Dervieux, C., & Woodhull, G. (2024). *Quarto* (Version 1.7.23) [Computer software]. https://doi.org/10.5281/zenodo.5960048

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*(1), 1–28. https://doi.org/10.18637/jss.v080.i01

Celniker, J. B., Gregory, A., Koo, H. J., Piff, P. K., Ditto, P. H., & Shariff, A. F. (2023). The moralization of effort. *Journal of Experimental Psychology: General*, *152*(1), 60–79. https://doi.org/10.1037/xge0001259

Cubitt, R. P., Drouvelis, M., Gächter, S., & Kabalin, R. (2011). Moral judgments in social dilemmas: How bad is free riding? *Journal of Public Economics*, *95*(3), 253–264. https://doi.org/10.1016/j.jpubeco.2010.10.011

Department for Science, Innovation & Technology. (2024). *Public attitudes to data and AI: Tracker survey (Wave 4) report*. https://www.gov.uk/government/publications/public-attitudes-to-data-and-ai-tracker-survey-wave-4/public-attitudes-to-data-and-ai-tracker-survey-wave-4-report

Earp, B. D., Porsdam Mann, S., Liu, P., Hannikainen, I., Khan, M. A., Chu, Y., & Savulescu, J. (2024). Credit and blame for AI-generated content: Effects of personalization in four countries. *Annals of the New York Academy of Sciences*, *1542*(1), 51–57. https://doi.org/10.1111/nyas.15258

Everett, J. A., & Kahane, G. (2020). Switching tracks? Towards a multidimensional model of utilitarian psychology. *Trends in Cognitive Sciences*, *24*(2), 124–134. https://doi.org/10.1016/j.tics.2019.11.012

Everett, J. A., Pizarro, D. A., & Crockett, M. J. (2016). Inference of trustworthiness from intuitive moral judgments. *Journal of Experimental Psychology: General*, *145*(6), 772–787.

https://doi.org/10.1037/xge0000165

Fiske, A. P. (1992). The four elementary forms of sociality: Framework for a unified theory of social relations. *Psychological Review*, *99*(4), 689–723. https://doi.org/10.1037/0033-295X.99.4.689

Fiske, S. T., Cuddy, A. J., & Glick, P. (2007). Universal dimensions of social cognition: Warmth and competence. *Trends in Cognitive Sciences*, *11*(2), 77–83. https://doi.org/10.1016/j.tics.2006.11.005

Goodman, R. (2010). Cognitive enhancement, cheating, and accomplishment. *Kennedy Institute of Ethics Journal*, *20*(2), 145–160. https://doi.org/10.1353/ken.0.0309

Goodwin, G. P., Piazza, J., & Rozin, P. (2014). Moral character predominates in person perception and evaluation. *Journal of Personality and Social Psychology*, *106*(1), 148–168. https://doi.org/10.1037/a0034726

Heider, F. (1958). *The psychology of interpersonal relations*. John Wiley & Sons Inc. https://doi.org/10.1037/10628-000

Kahane, G., Everett, J. A., Earp, B. D., Caviola, L., Faber, N. S., Crockett, M. J., & Savulescu, J. (2018). Beyond sacrificial harm: A two-dimensional model of utilitarian psychology. *Psychological Review*, *125*(2), 131–164. https://doi.org/10.1037/rev0000093

Kerr, N. L. (1983). Motivation losses in small groups: A social dilemma analysis. *Journal of Personality and Social Psychology*, *45*(4), 819–828. https://doi.org/10.1037/0022-3514.45.4.819

Kruger, J., Wirtz, D., Van Boven, L., & Altermatt, T. W. (2004). The effort heuristic. *Journal of Experimental Social Psychology*, *40*(1), 91–98. https://doi.org/10.1016/S0022-1031(03)00065-9

Landau, W. M. (2021). The targets R package: A dynamic Make-like function-oriented pipeline toolkit for reproducibility and high-performance computing. *Journal of Open Source Software*, *6*(57), 2959. https://doi.org/10.21105/joss.02959

Landes, E., & Everett, J. A. C. (2025). *AI should develop human empathy, not replace it*.

PsyArXiv. https://doi.org/10.31234/osf.io/y3qzu_v1

Liu, B., Kang, J., & Wei, L. (2024). Artificial intelligence and perceived effort in relationship maintenance: Effects on relationship satisfaction and uncertainty. *Journal of Social and Personal Relationships*, *41*(5), 1232–1252. https://doi.org/10.1177/02654075231189899

Malle, B. F. (2022). Attribution theories. In *Theories in social psychology, second edition* (pp. 93–120). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781394266616.ch4

Medaglia, J. D., Yaden, D. B., Helion, C., & Haslam, M. (2019). Moral attitudes and willingness to enhance and repair cognition with brain stimulation. *Brain Stimulation*, *12*(1), 44–53. https://doi.org/10.1016/j.brs.2018.09.014

miramar0. (2024). *My (30F) husband (36M) used AI to write his vows. How do I approach him about this?* [Online forum post]. Reddit. https://www.reddit.com/r/relationship_advice/comments/1d9tw9j/my_30f_husband_36m_used_ai_to_write_his_vows_how/

Newman, G. E. (2019). The psychology of authenticity. *Review of General Psychology*, *23*(1), 8–18. https://doi.org/10.1037/gpr0000158

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, *381*(6654), 187–192. https://doi.org/10.1126/science.adh2586

Oxford Insights. (2024). *Government AI readiness index*. https://oxfordinsights.com/ai-readiness/ai-readiness-index/

Pedersen, T. L. (2025). *patchwork: The composer of plots*. https://patchwork.data-imaginist.com

Pugh, A. J. (2024). *The last human job: The work of connecting in a disconnected world*. Princeton University Press.

R Core Team. (2022). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Roth, L. H. O., & Tissot, T. (2025). *A costly co-pilot? AI usage signals reduced morality via effort perceptions*. OSF Preprints. https://doi.org/10.31219/osf.io/vwxgz_v1

Rudski, J. M. (2014). A comparison of attitudes toward pharmacological treatment versus enhancement under competitive and noncompetitive conditions. *AJOB Empirical Bioethics*, *5*(2), 80–90. https://doi.org/10.1080/23294515.2013.850122

Stohr, K. (2006). Contemporary virtue ethics. *Philosophy Compass*, *1*(1), 22–27. https://doi.org/10.1111/j.1747-9991.2006.00004.x

Tortoise Media. (2024). *The global AI index*. https://www.tortoisemedia.com/data/global-ai

Vallor, S. (2015). Moral deskilling and upskilling in a new machine age: Reflections on the ambiguous future of character. *Philosophy & Technology*, *28*, 107–124. https://doi.org/10.1007/s13347-014-0156-9

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org

Supplementary Materials

Negative Perceptions of Outsourcing to Artificial Intelligence

Scott Claessens, Pierce Veitch, and Jim Everett

School of Psychology, University of Kent

Pilot Study 1

Methods

Participants

We recruited a convenience sample of 200 participants from the United Kingdom through Prolific. After excluding participants who failed our pre-treatment attention check, we were left with a final sample of 186 participants (118 female; 67 male; 1 non-binary / third gender; 0 undisclosed gender; mean age = 38.99 years).

Procedure

We presented participants with six different tasks "that people might perform in their daily lives". The six tasks were randomly drawn from a larger set of 20 tasks (see Supplementary Table 1 for the full list of tasks). For each task, we asked participants the following questions on 7-point Likert scales:

- Is this a social task?
- Does this task require social skills?
- Does this task impact other people?
- How important are the consequences of this task?
- How important is it that effort goes into this task?
- How important is it that others see the effort that goes into this task?

Statistical Analysis

We fitted a Bayesian multivariate multilevel cumulative-link ordinal model to the data using the *brms* R package. We modelled each task evaluation as a separate response variable and included correlated varying intercepts for participants and tasks. We used regularising priors for all parameters to impose conservatism on parameter estimates (see Supplementary Materials for full model specification). The model converged normally ($\hat{R} \leq 1.01$).

Results

We found that participants' responses to all six questions tended to be positively correlated. For example, tasks rated as more social were also rated as requiring more social skills (see Supplementary Figure 14). Estimated averages and rankings for the 20 tasks across each of the questions can be found in Supplementary Figures 15 – 20.

Pilot Study 2

Methods

Participants

We conducted a power simulation to determine our target sample size. The simulation suggested that a sample size of 150 participants per condition (overall $n = 450$ for three conditions) would be required to detect a small difference between conditions (Cohen's $d \approx 0.20$) with above 80% power.

We recruited a convenience sample of 500 participants from the United Kingdom through Prolific. After excluding participants who failed our pre-treatment attention check, we were left with a final sample of 466 participants (292 female; 169 male; 4 non-binary / third gender; 1 undisclosed gender; mean age = 42.32 years). 73% of these participants reported having used ChatGPT before (see Supplementary Figure 21).

Design

We randomly allocated participants into one of three conditions in a between-subjects design: (*i*) the control condition, (*ii*) the AI outsourcing condition, or (*iii*) the human outsourcing condition. These conditions determined how scenarios were presented to participants.

Procedure

We presented participants with six scenarios. Each scenario described a person completing a task, such as writing computer code or writing a love letter. The six tasks were randomly drawn from a larger set of 20 tasks (see Supplementary Table 1 for the full list of tasks). For each scenario, we told participants:

- *Control condition*: "In order to complete this task, [the person] works on it by themselves from start to finish."
- *AI outsourcing condition*: "In order to complete this task, [the person] gets the AI tool ChatGPT to do it for them."

- *Human outsourcing condition*: "In order to complete this task, [the person] gets someone else to do it for them."

We then asked participants how well each of the following words described the person in the scenario: competent, warm, moral, lazy, and trustworthy. Participants answered these questions on 7-point Likert scales, ranging from "does not describe [the person] well" to "describes [the person] extremely well".

After the six scenarios, we asked participants several questions about the AI tool ChatGPT, including their familiarity with ChatGPT, whether they had used ChatGPT before, how frequently they used ChatGPT, and how trustworthy they thought ChatGPT was (see Supplementary Figure 21).

Pre-registration

We pre-registered the study on the Open Science Framework (https://osf.io/khr42).

Statistical Analysis

We fitted Bayesian multivariate multilevel cumulative-link ordinal models to the data using the *brms* R package. We modelled each character evaluation – competence, warmth, morality, laziness, and trustworthiness – as a separate response variable and included fixed effects for conditions, varying intercepts for participants, and varying intercepts and slopes for tasks. We used regularising priors for all parameters to impose conservatism on parameter estimates (see Supplementary Materials for full model specifications). All models converged normally ($\hat{R} \leq 1.01$).

Results

We found that people who outsourced tasks to AI or other humans were perceived more negatively than people who completed the tasks themselves (Supplementary Figure 22). In particular, people who outsourced were perceived as lazier and less competent, with smaller yet detectable differences for perceptions of warmth, morality, and trustworthiness (Supplementary Table 8). Across all measures, outsourcing to other humans was perceived more negatively than outsourcing to AI.

We found that the effects of outsourcing varied across the different tasks, especially for perceptions of warmth and morality (Supplementary Figure 23). For example, people were perceived as less warm if they outsourced writing a love letter, but not if they outsourced writing computer code. Similarly, people were perceived as less moral if they outsourced writing an apology letter to a friend, but not if they outsourced writing a dinner recipe. By contrast, the effects of outsourcing on competence, laziness, and trustworthiness were more consistent across tasks.

To determine the factors that predict variation across tasks, we incorporated ratings of tasks from the first pilot study. Participants were asked to rate the 20 tasks on several features: whether the task is social, requires social skills, impacts others, has important consequences, and requires effort. All of these features predicted stronger causal effects of outsourcing compared to control (Supplementary Figures 24 and 25). In other words, outsourcing to AI or other humans is perceived more negatively for tasks that have these features, compared to tasks without these features.

Vignette Wording in Study 5

We presented participants in Study 5 with the following vignette text:

> Adam has been dating his partner for almost a year, and Valentine's Day is coming up. He knows that many people exchange a card on Valentine's Day containing a love letter to their partner, and he decides to send a love letter to his partner too.
>
> This year, Adam has been closely following developments in technology and has read of people using AI tools like ChatGPT for things like this, either using it to help with writing or getting AI to do the task completely.

This was followed by the manipulation text (see main text). Participants were then presented with the love letter that Adam ostensibly wrote, which was held constant across conditions:

> Happy Valentine's Day, my love.
>
> I don't think I tell you enough just how much you mean to me. Being with you feels like breathing a little easier, like the world is a bit softer just because you're in it. You make the everyday feel special, and somehow you always know how to calm my nerves or make me laugh at just the right moment. I feel like myself with you – maybe even a better version of myself – and that's such a rare and beautiful thing.
>
> I'm so grateful for you – for the way you listen, the way you love, the way you show up, even in the small ways. I hope you know that no matter what, I'm always in your corner. I can't wait to keep making memories together, whether we're off on some adventure or just curled up on the couch. I love you more than I can really put into words, but I promise I'll spend every day trying.
>
> Yours,
>
> Adam

Methods for Text Analysis in Study 5

To generate frequency lists for each experimental condition in Study 5, we created three documents containing the raw text submissions to the open-ended question “In your own words, describe how you feel about Adam and why”. Each raw text submission was paired with a numbered text ID column. The number of submissions was roughly equivalent across conditions: the control condition (N = 196), the tool outsourcing condition (N = 215), and the full outsourcing condition (N = 202).

All text processing was conducted using the Basic Unit-Transposable Text Experimentation Resource (BUTTER; Version 0.9.4.1; Boyd, 2019). To prepare the data, each CSV file was converted into a folder containing individual text files – one per submission – using two plugins: *Read Text from CSV* (Version 1.0.2) and *Save .txt Files to Folder* (Version 1.0.6). The settings for *Read Text from CSV* were as follows: file encoding = UTF-8, row identifier = ID, text column = Text, CSV delimiter = , and CSV quote = “.

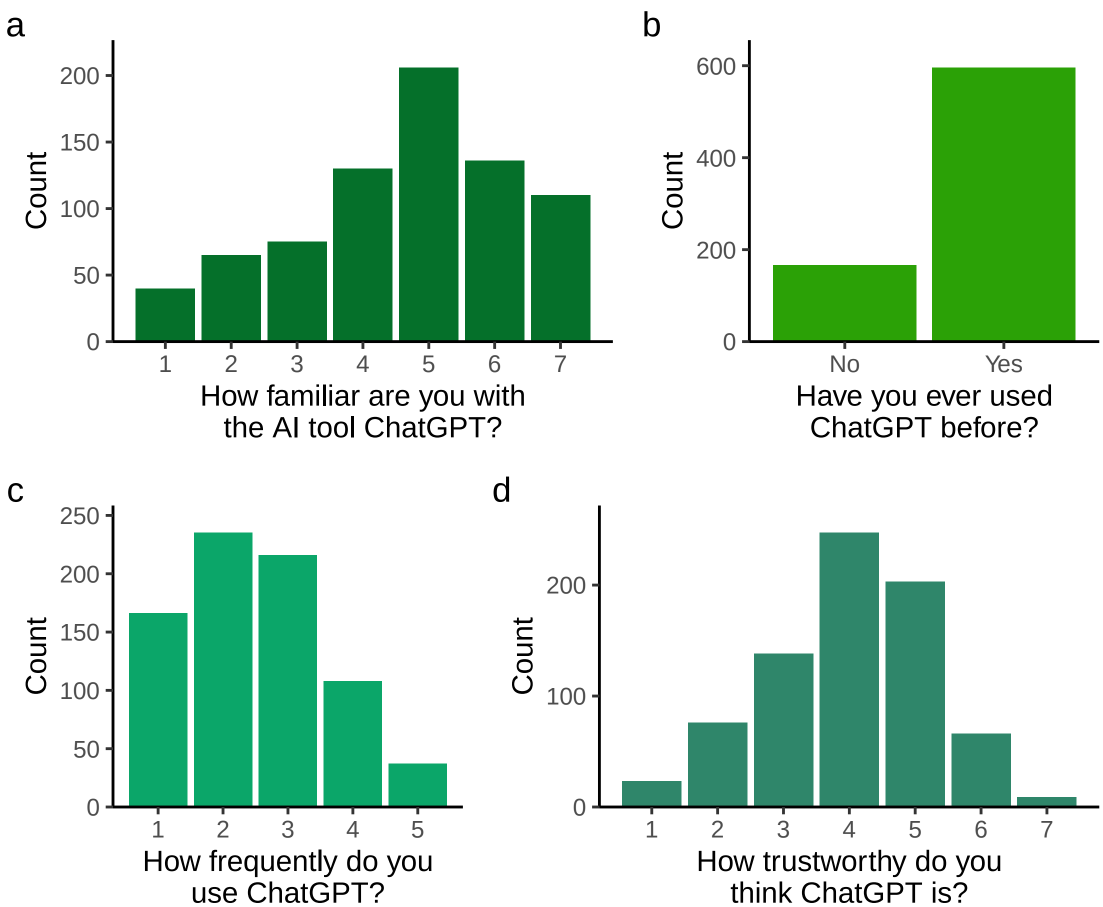
To generate frequency lists, we first loaded the .txt files using the *Load .txt Files from Folder* plugin (Version 1.0.4). Tokenization was performed using the Twitter-Aware Tokenizer (Version 1.0.2), with the options *convert text to lowercase* and *reduce elongation* enabled to minimize superficial variation in tokens. We removed filler and function words using the *Remove Stop Words* plugin (Version 1.0.31), applying the default English stop word list.

Frequency lists were created with the *Frequency List* plugin (Version 1.0.11). Settings included: unigram analysis (N = 1), omission of n-grams with frequency < 5, exclusion of n-grams appearing in fewer than 0.1% of documents, filtering collocates by Normalized Pointwise Mutual Information (NPMI), and removal of collocates with metric values < 0.5. Outputs were saved using the *Save Output to CSV* plugin (Version 1.0.5). This process was repeated separately for each condition folder.

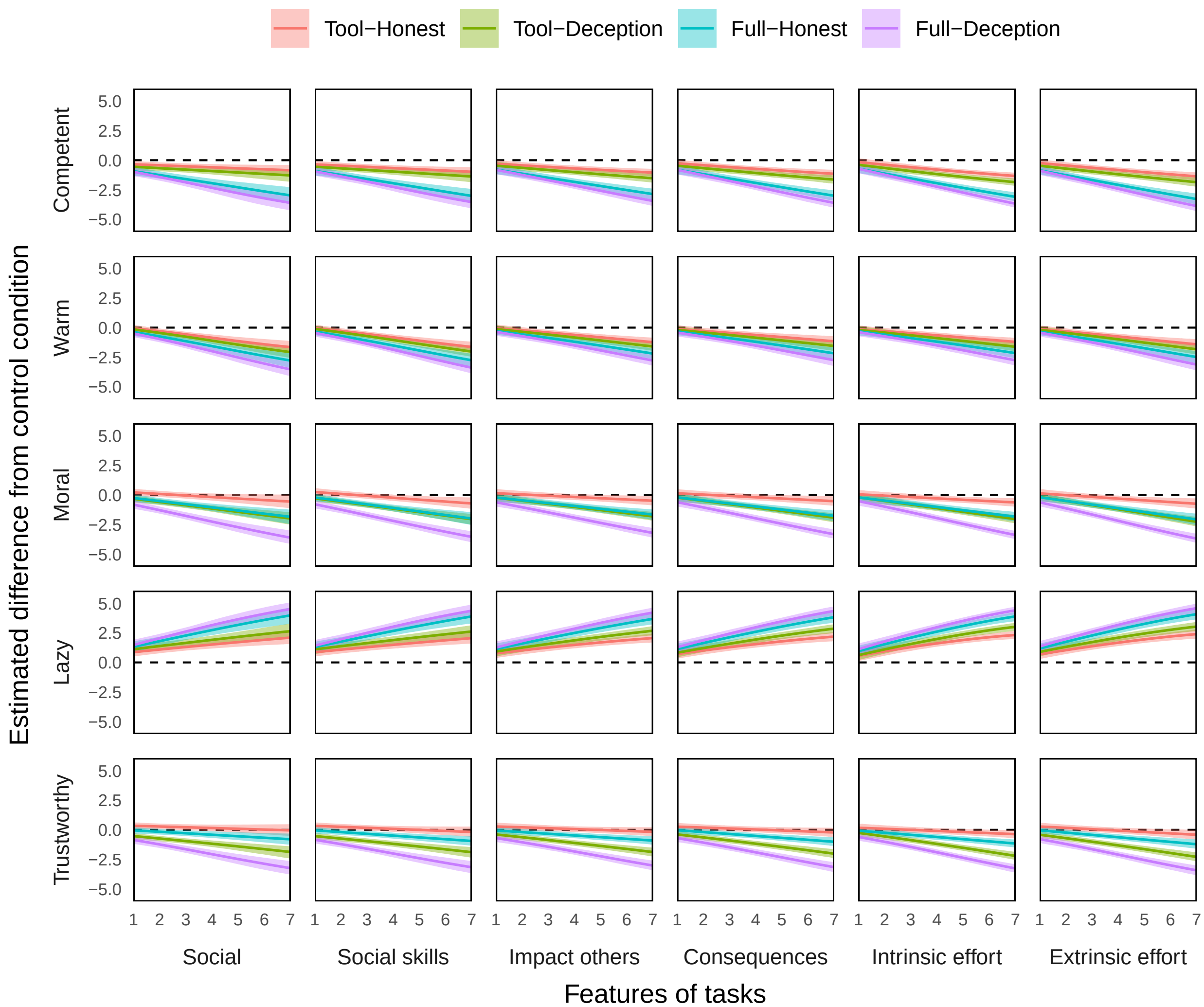
For cross-condition comparison, we used the *Compare Frequencies* plugin (Version 1.1.02), retaining most default settings. The only modification was disabling the *Skip comparisons with 0 frequency values* option. This plugin calculates a range of comparative metrics, including log likelihood (LL), %DIFF, Bayes Information Criterion (BIC), relative risk (RRisk), log ratio, and odds ratio.

Following previous work (e.g., Rayson & Garside, 2000; Gregson et al., 2022), we interpret %DIFF as an indicator of effect size and direction. Frequentist statistical significance was determined using log likelihood values, with the following thresholds: LL ≥ 3.84 ($p < .05$), LL ≥ 6.63 ($p < .01$), LL ≥ 10.83 ($p < .001$), and LL ≥ 15.13 ($p < .0001$).

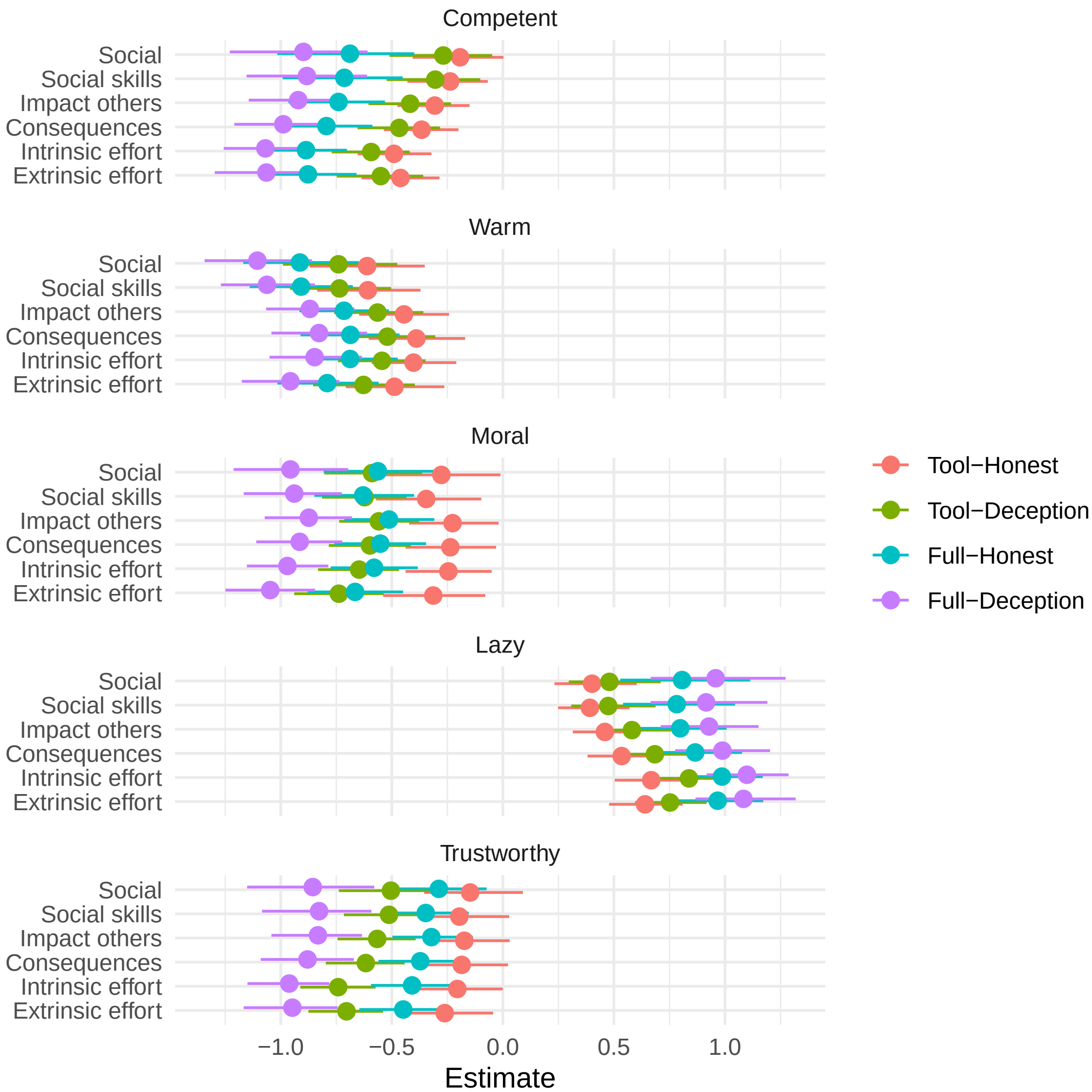
Supplementary Figures



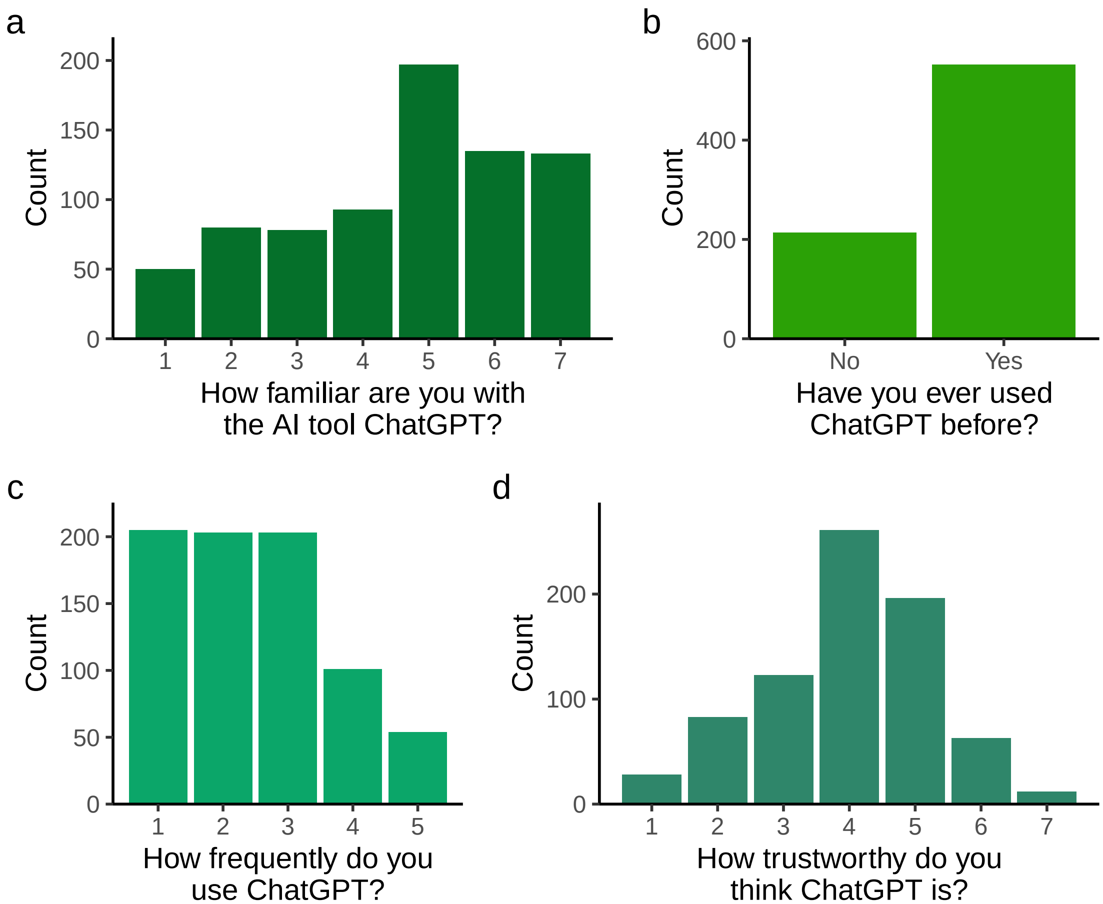
Supplementary Figure 1: Responses to the questions about ChatGPT in Study 1.



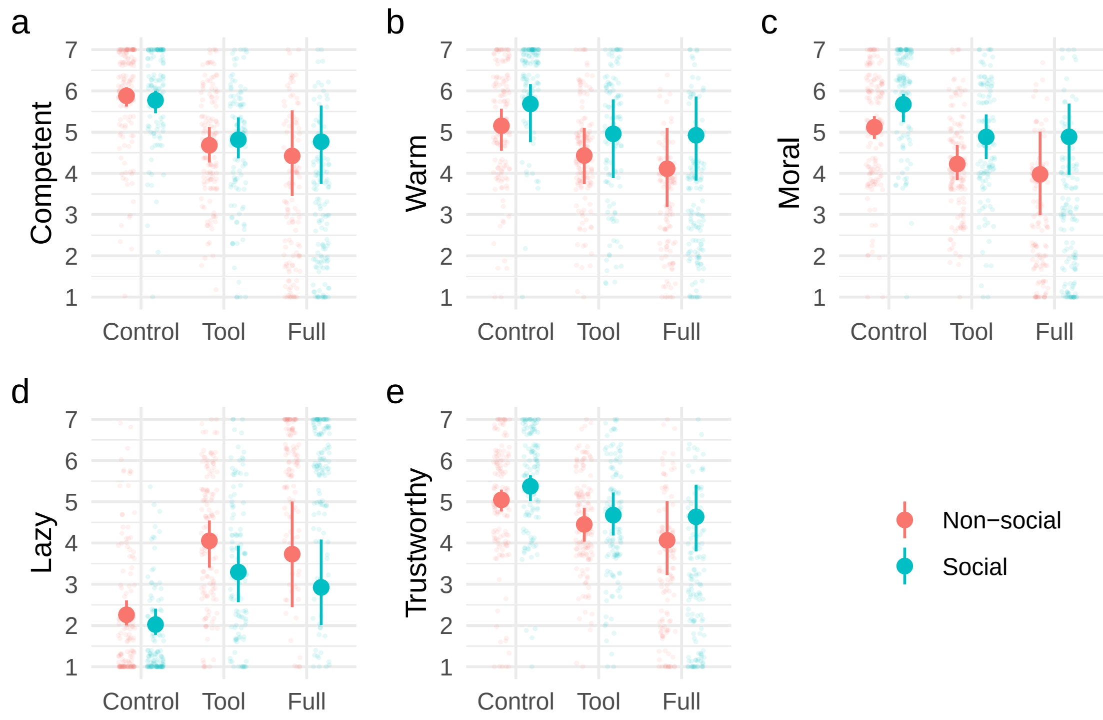
Supplementary Figure 2: The impact of task-specific features (e.g., being a social task) on the causal effects of outsourcing to AI compared to the control condition in Study 1. The y-axis reflects the estimated differences between the experimental conditions and the control condition (dashed line) on a 7-point Likert scale. Lines and shaded areas represent posterior medians and 95% credible intervals, respectively. The patterns indicate, for example, more negative effects of outsourcing on character evaluations for tasks that are rated as more social.



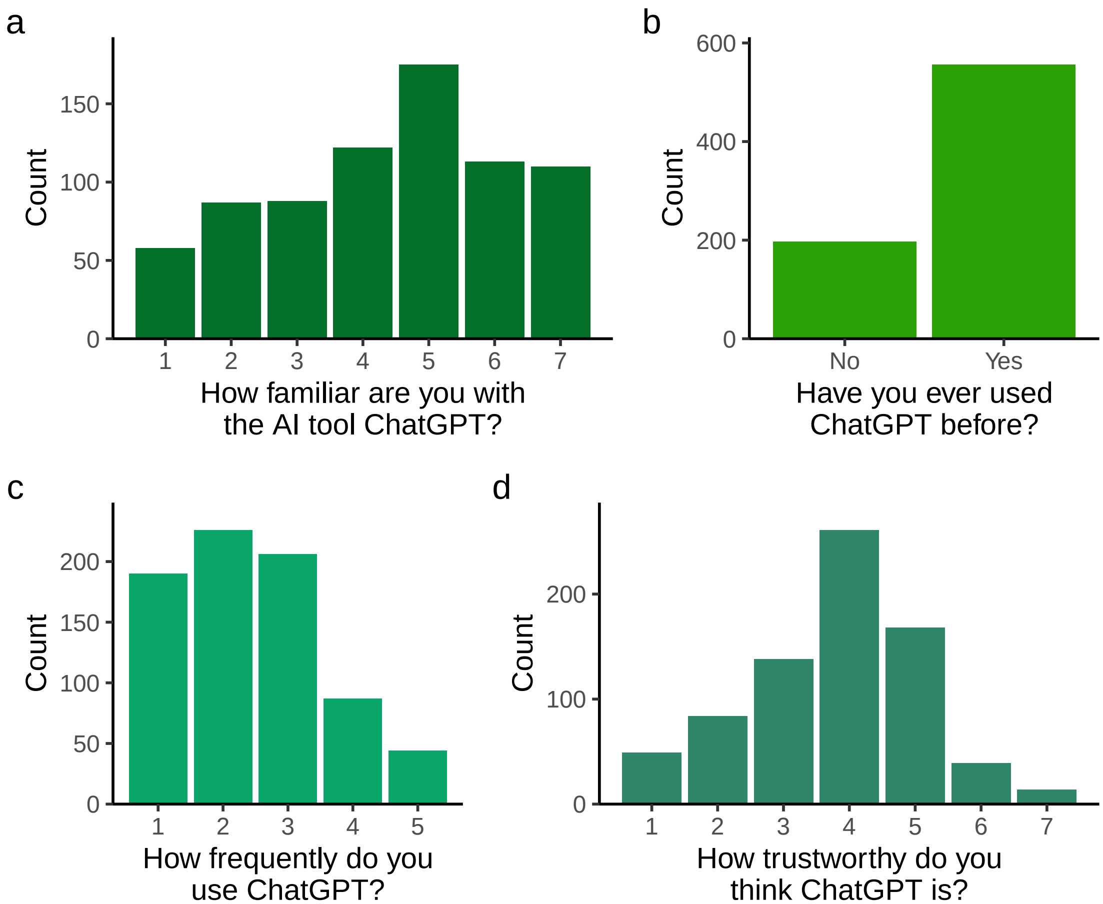
Supplementary Figure 3: Interaction parameters from models including task-specific features as moderators of the causal effects of AI outsourcing compared to the control condition in Study 1. Points and line ranges represent posterior medians and 95% credible intervals, respectively.



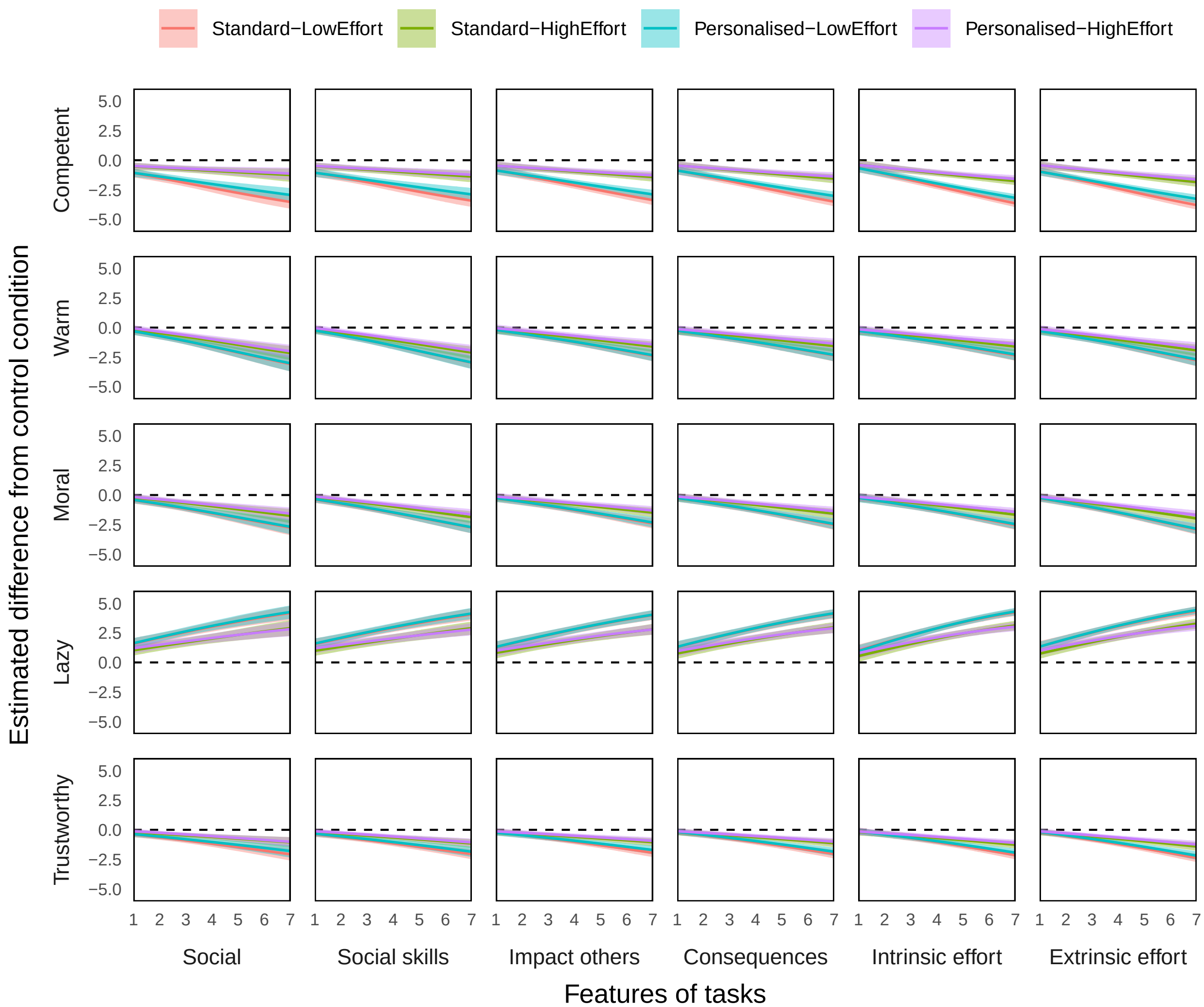
Supplementary Figure 4: Responses to the questions about ChatGPT in Study 2.



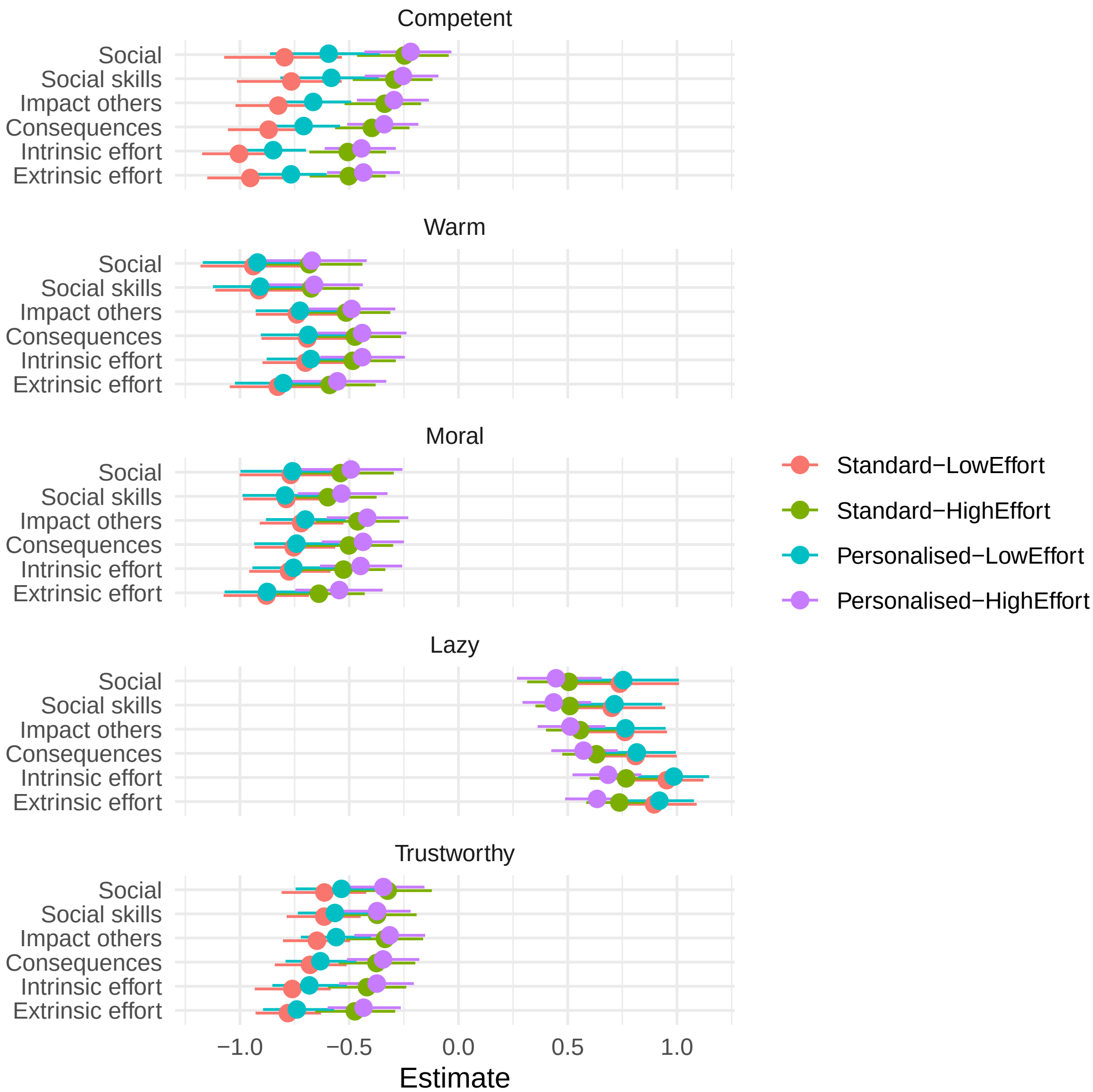
Supplementary Figure 5: Character evaluations in Study 2. Participants in the control condition, the tool outsourcing condition, and the full outsourcing condition evaluated the "other participant" on (a) competence, (b) warmth, (c) morality, (d) laziness, and (e) trustworthiness. Jittered points represent participant responses to the questions, split by whether the writing task was a non-social task (red) or a social task (blue). Point ranges are estimated marginal means from the fitted model, pooling over essay answers. Points and line ranges represent posterior medians and 95% credible intervals, respectively.



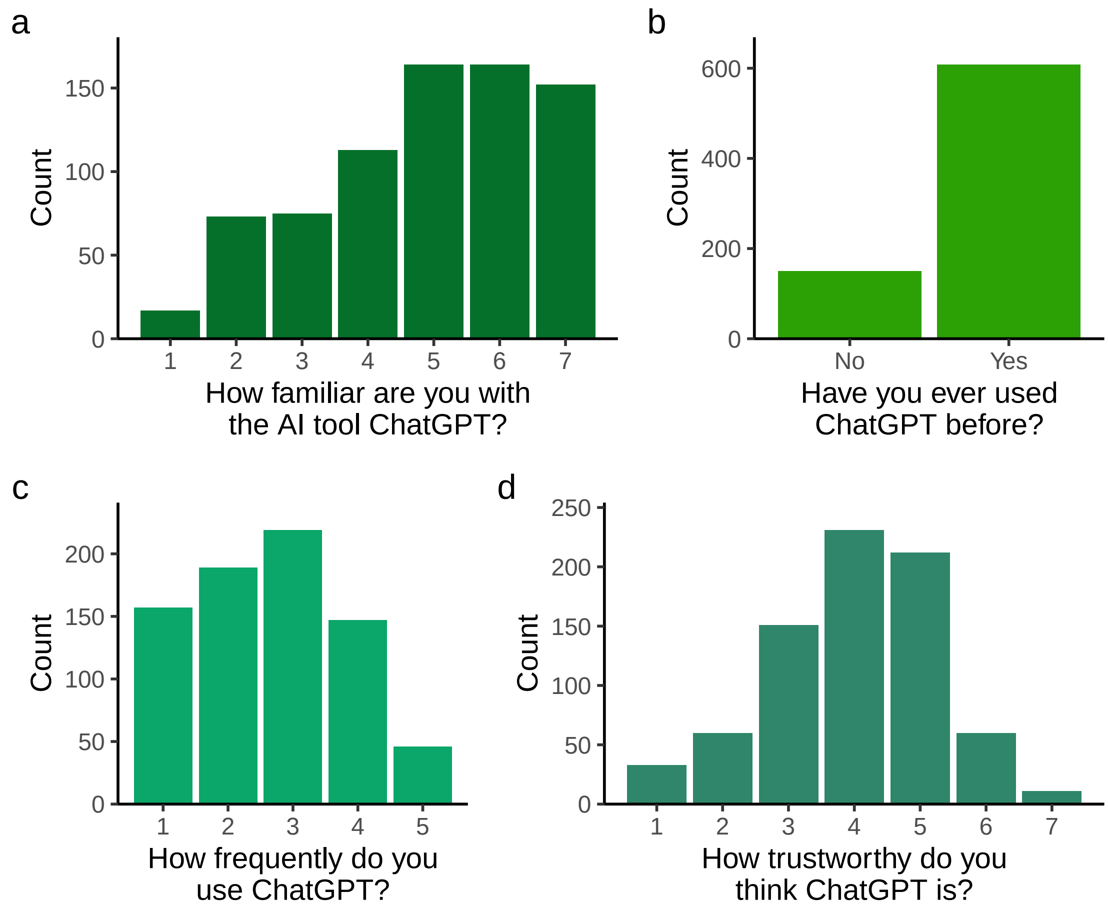
Supplementary Figure 6: Responses to the questions about ChatGPT in Study 3.



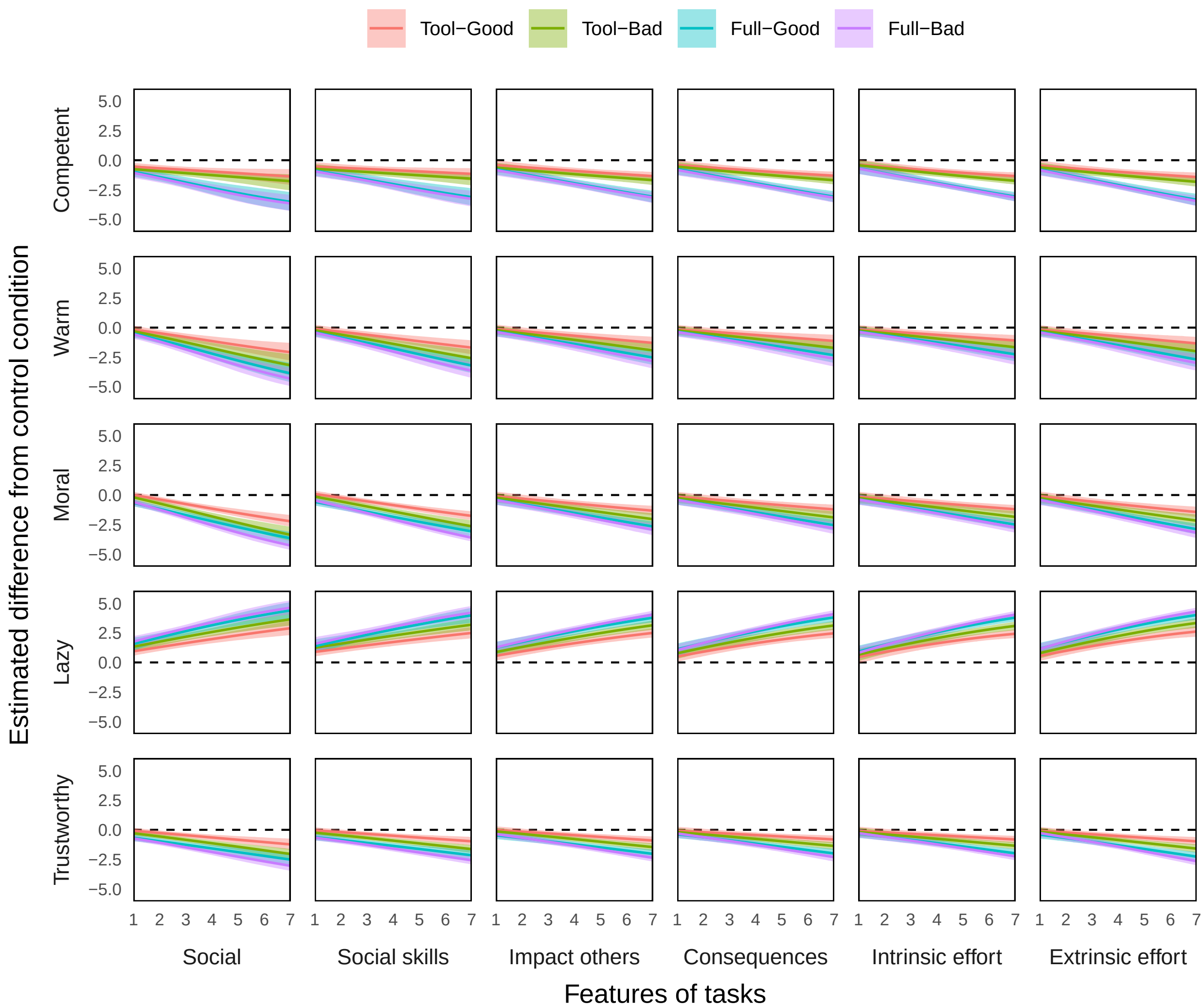
Supplementary Figure 7: The impact of task-specific features (e.g., being a social task) on the causal effects of outsourcing to AI compared to the control condition in Study 3. The y-axis reflects the estimated differences between the experimental conditions and the control condition (dashed line) on a 7-point Likert scale. Lines and shaded areas represent posterior medians and 95% credible intervals, respectively. The patterns indicate, for example, more negative effects of outsourcing on character evaluations for tasks that are rated as more social.



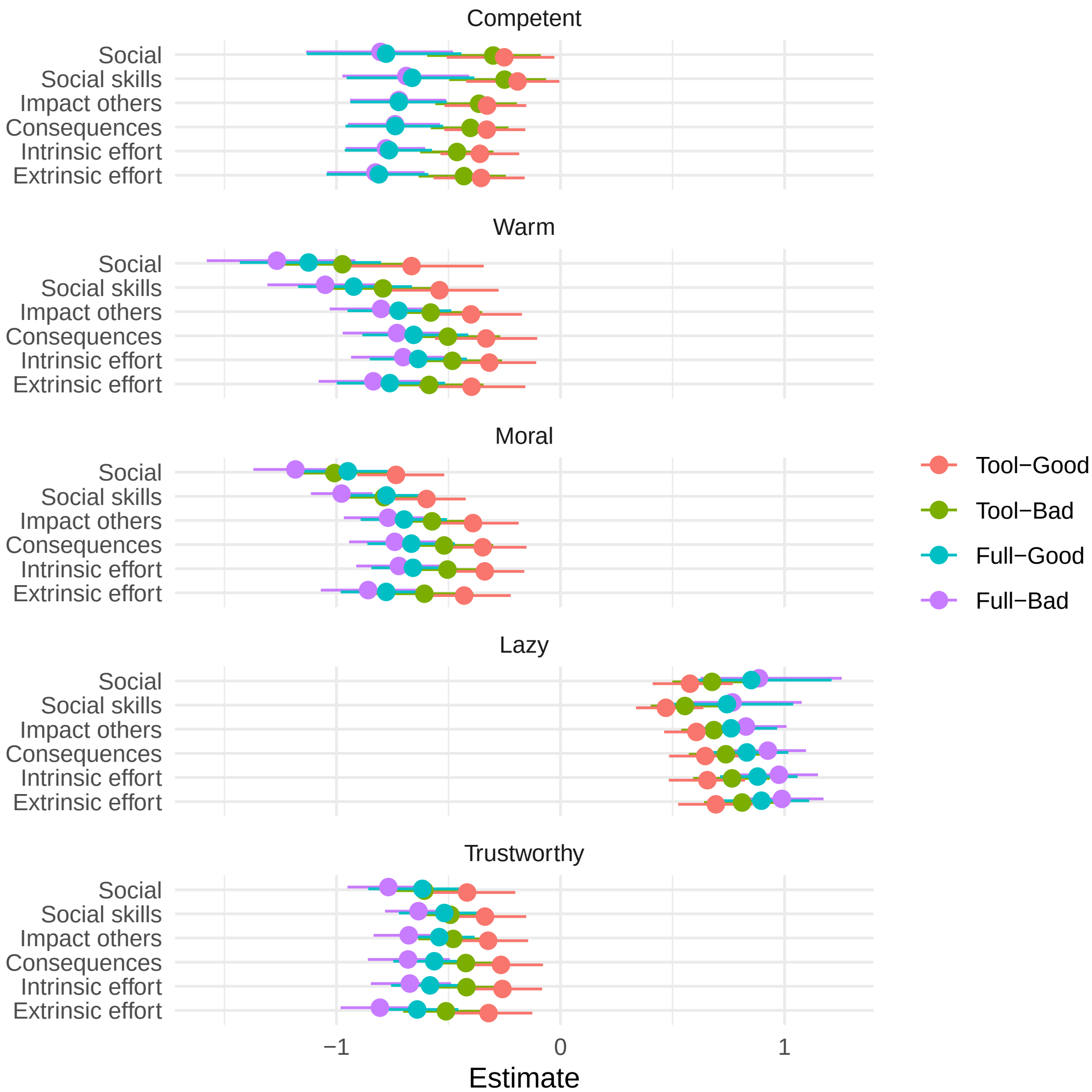
Supplementary Figure 8: Interaction parameters from models including task-specific features as moderators of the causal effects of AI outsourcing compared to the control condition in Study 3. Points and line ranges represent posterior medians and 95% credible intervals, respectively.



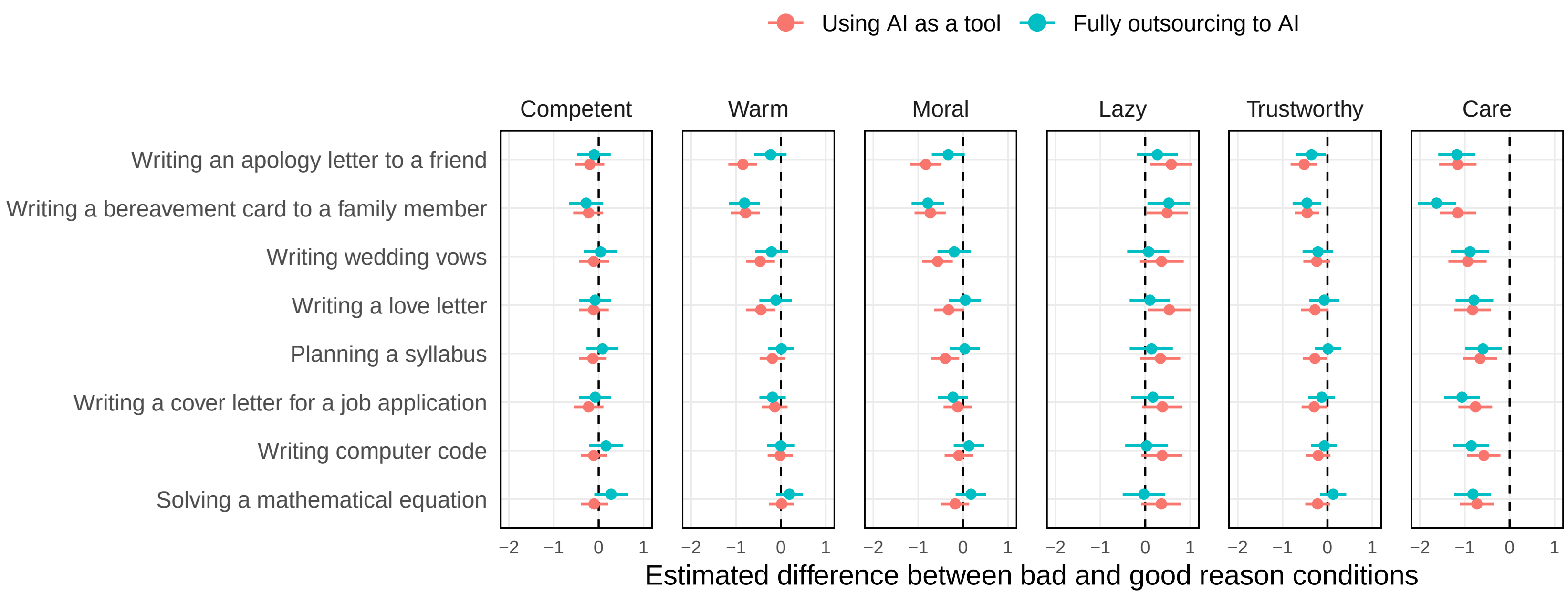
Supplementary Figure 9: Responses to the questions about ChatGPT in Study 4.



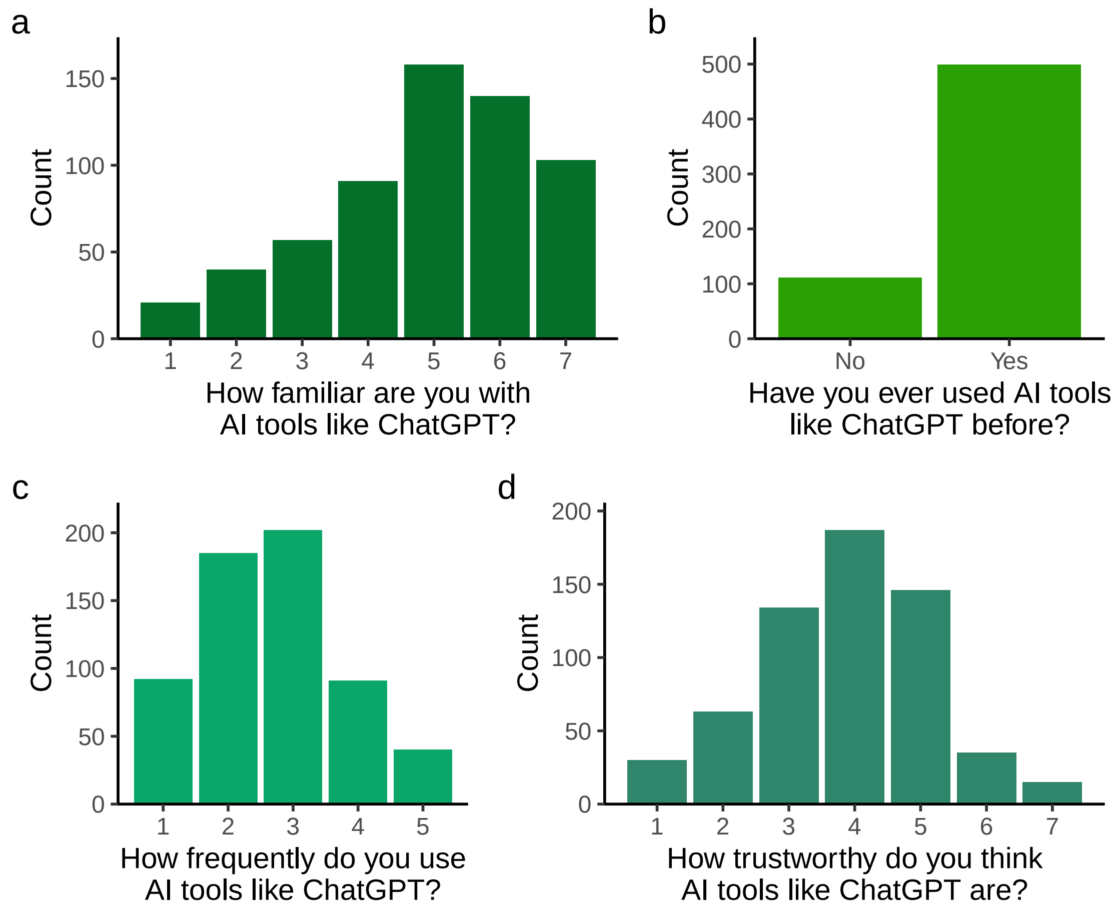
Supplementary Figure 10: The impact of task-specific features (e.g., being a social task) on the causal effects of outsourcing to AI compared to the control condition in Study 4. The y-axis reflects the estimated differences between the experimental conditions and the control condition (dashed line) on a 7-point Likert scale. Lines and shaded areas represent posterior medians and 95% credible intervals, respectively. The patterns indicate, for example, more negative effects of outsourcing on character evaluations for tasks that are rated as more social.



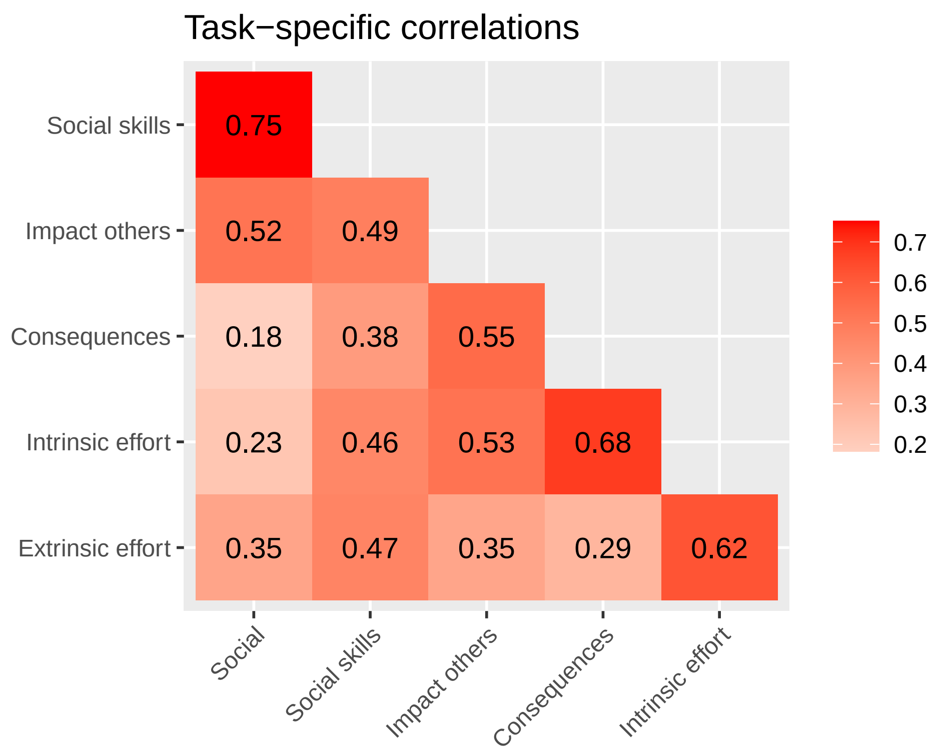
Supplementary Figure 11: Interaction parameters from models including task-specific features as moderators of the causal effects of AI outsourcing compared to the control condition in Study 4. Points and line ranges represent posterior medians and 95% credible intervals, respectively.



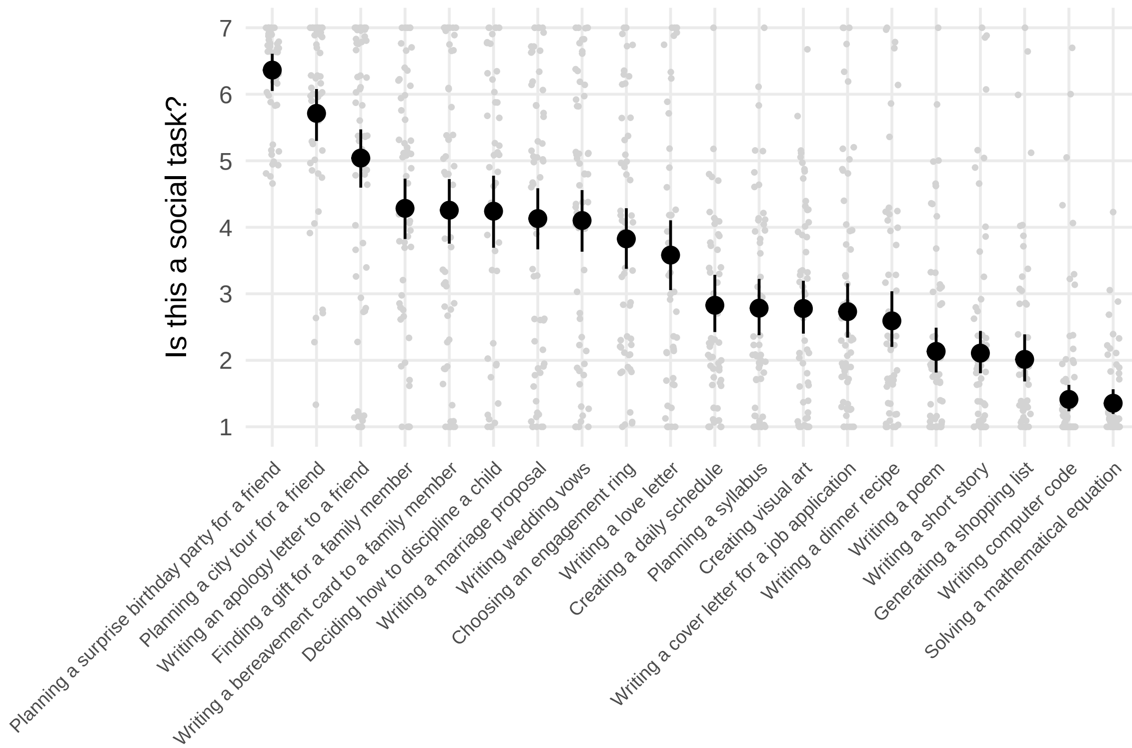
Supplementary Figure 12: Variation in the effect of reasons across tasks in Study 4. Tasks are ordered from most social (top) to least social (bottom) according to ratings from a pilot study. Point ranges are differences in marginal means on a 7-point Likert scale between the "bad reason" and "good reason" conditions, split by outsourcing type. Points and ranges represent posterior medians and 95% credible intervals, respectively.



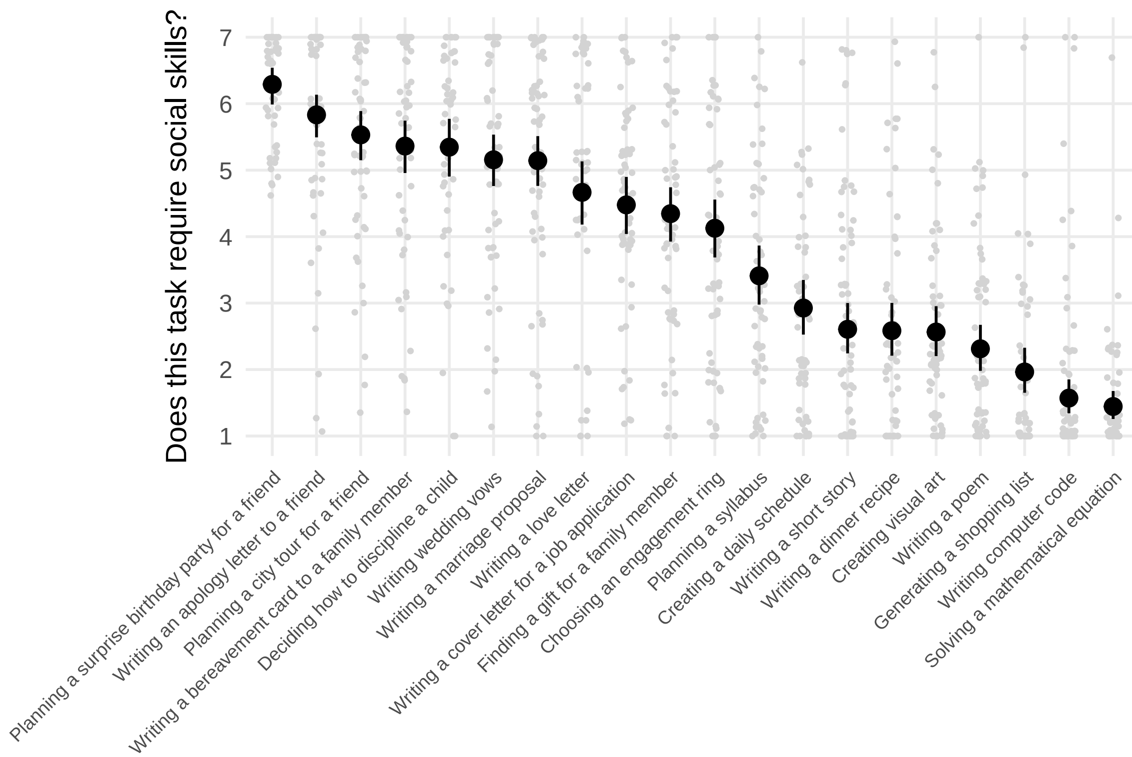
Supplementary Figure 13: Responses to the questions about ChatGPT in Study 5.



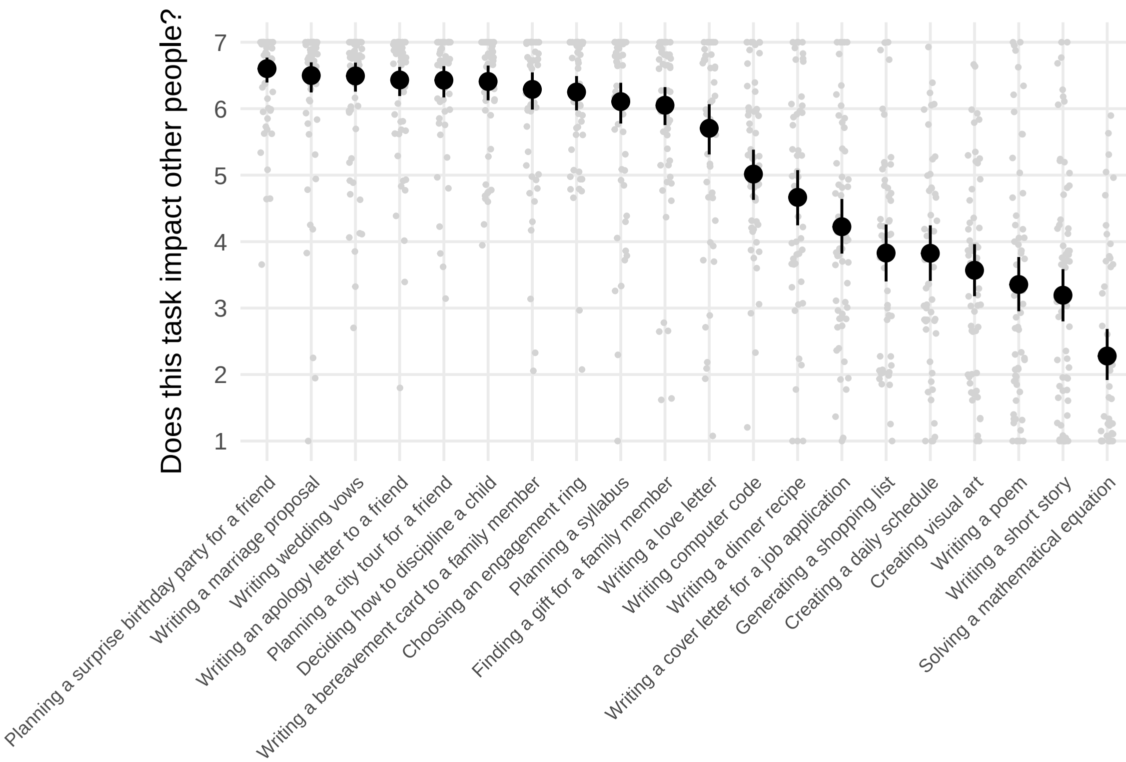
Supplementary Figure 14: Model-estimated task-specific correlations between all six questions in the first pilot study. Values are posterior median correlations. A positive correlation indicates that tasks that are rated highly on one question tend to be rated highly on another question.



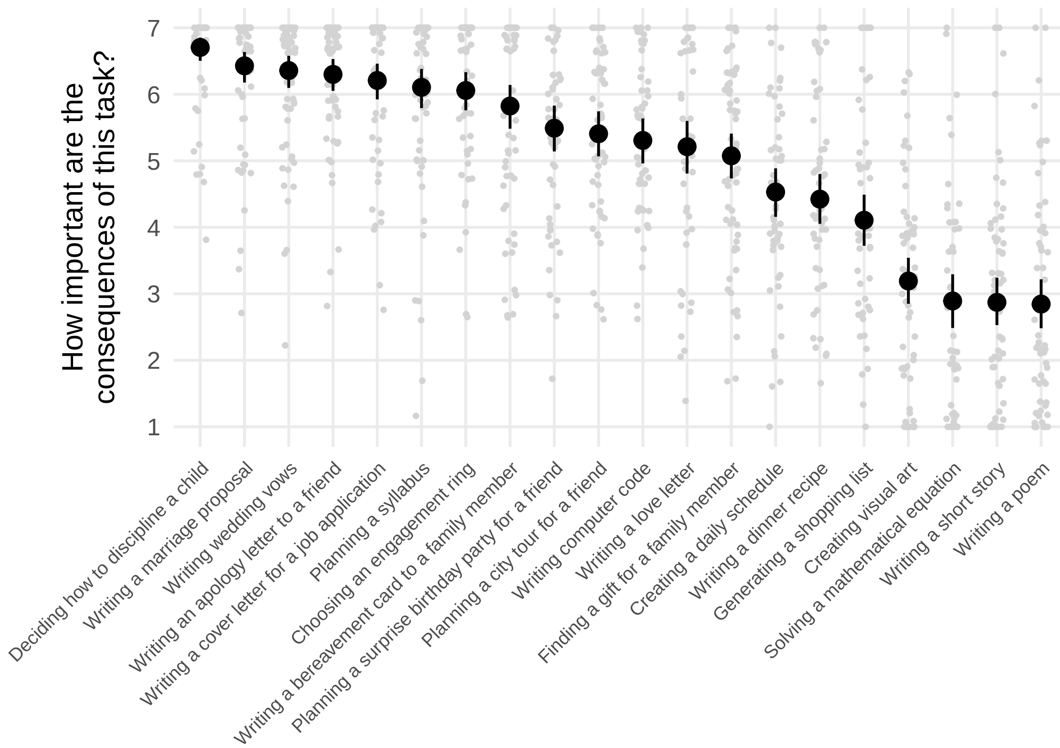
Supplementary Figure 15: Model-estimated means for the question "Is this a social task?" across all 20 tasks in the first pilot study. Grey points represent participant responses to the question, jittered for easier viewing. Black points are estimated means from the fitted model, pooling over participants. Black points and line ranges represent posterior medians and 95% credible intervals, respectively.



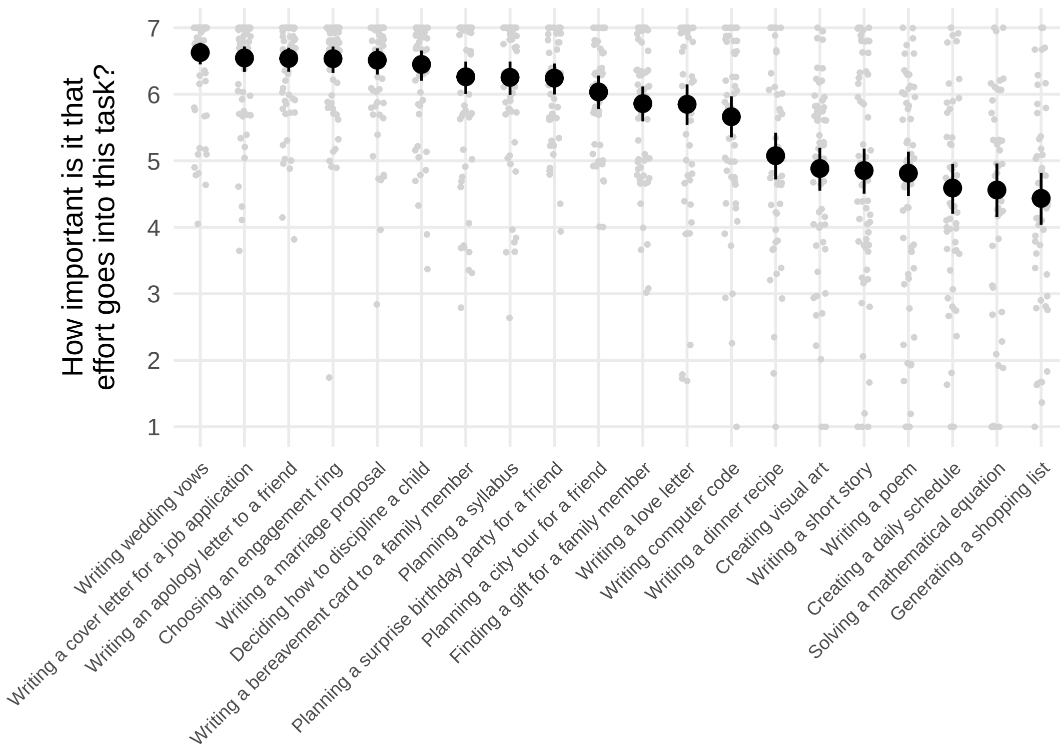
Supplementary Figure 16: Model-estimated means for the question "Does this task require social skills?" across all 20 tasks in the first pilot study. Grey points represent participant responses to the question, jittered for easier viewing. Black points are estimated means from the fitted model, pooling over participants. Black points and line ranges represent posterior medians and 95% credible intervals, respectively.



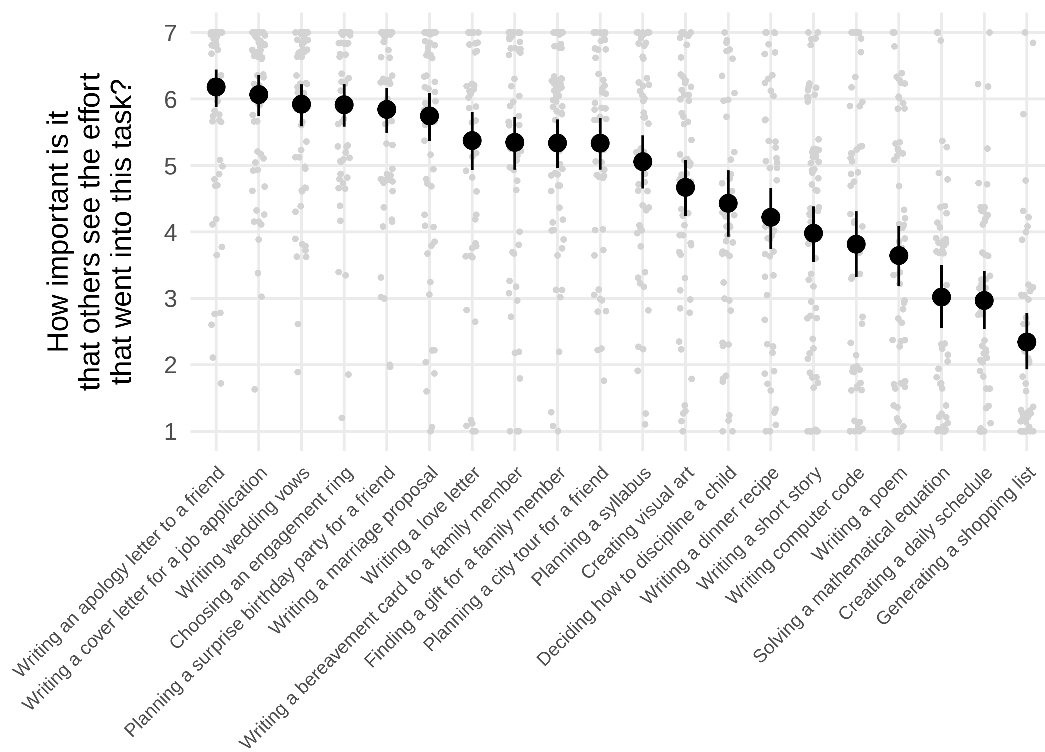
Supplementary Figure 17: Model-estimated means for the question "Does this task impact other people?" across all 20 tasks in the first pilot study. Grey points represent participant responses to the question, jittered for easier viewing. Black points are estimated means from the fitted model, pooling over participants. Black points and line ranges represent posterior medians and 95% credible intervals, respectively.



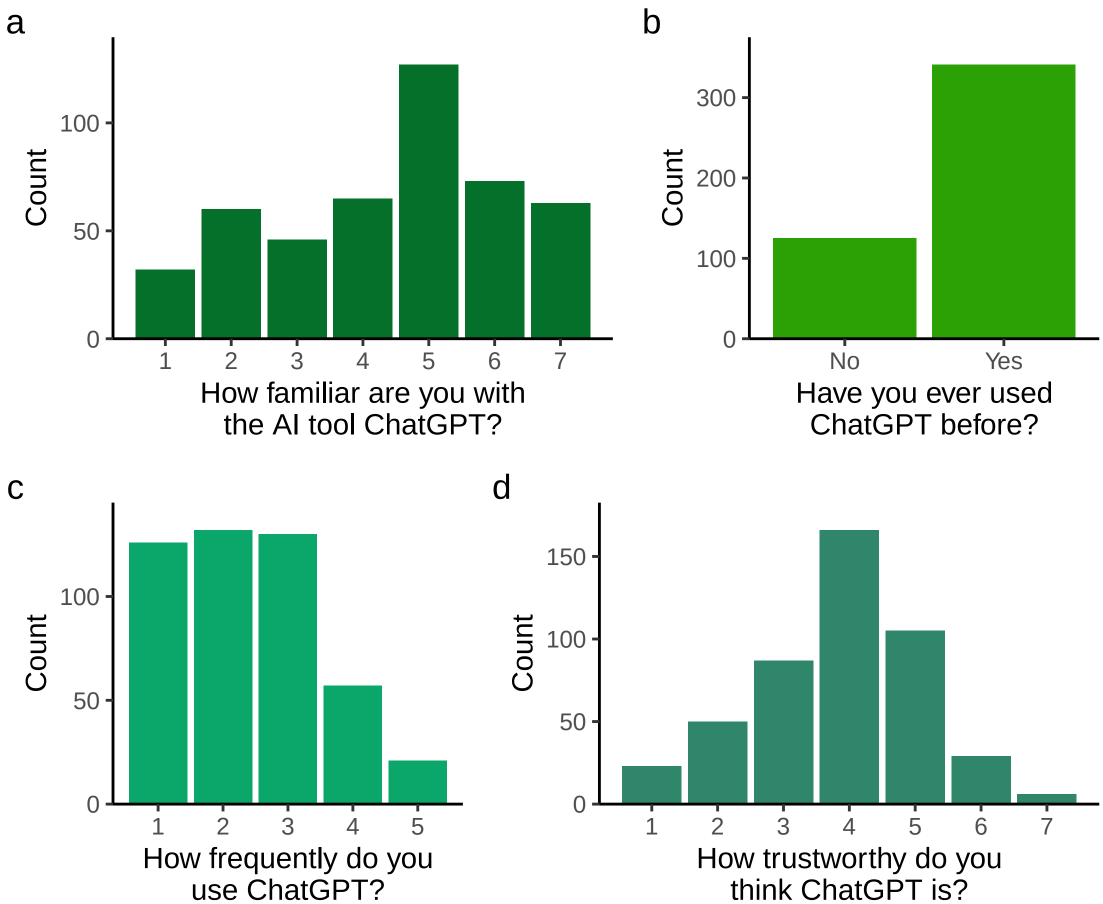
Supplementary Figure 18: Model-estimated means for the question "How important are the consequences of this task?" across all 20 tasks in the first pilot study. Grey points represent participant responses to the question, jittered for easier viewing. Black points are estimated means from the fitted model, pooling over participants. Black points and line ranges represent posterior medians and 95% credible intervals, respectively.



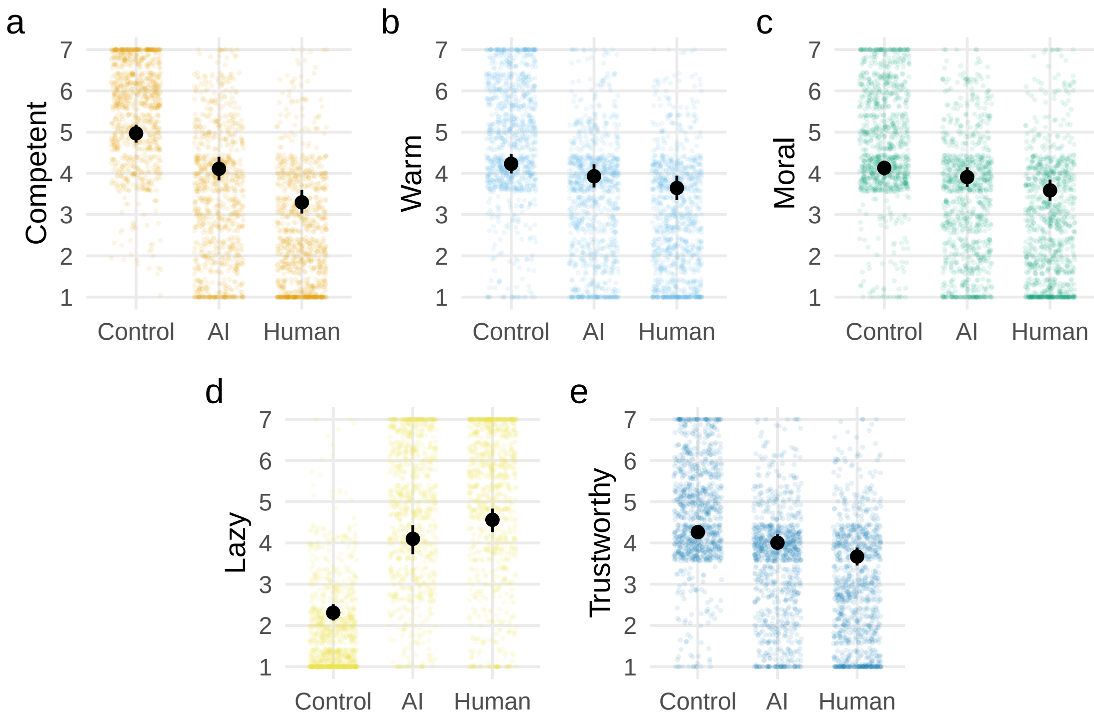
Supplementary Figure 19: Model-estimated means for the question "How important is it that effort goes into this task?" across all 20 tasks in the first pilot study. Grey points represent participant responses to the question, jittered for easier viewing. Black points are estimated means from the fitted model, pooling over participants. Black points and line ranges represent posterior medians and 95% credible intervals, respectively.



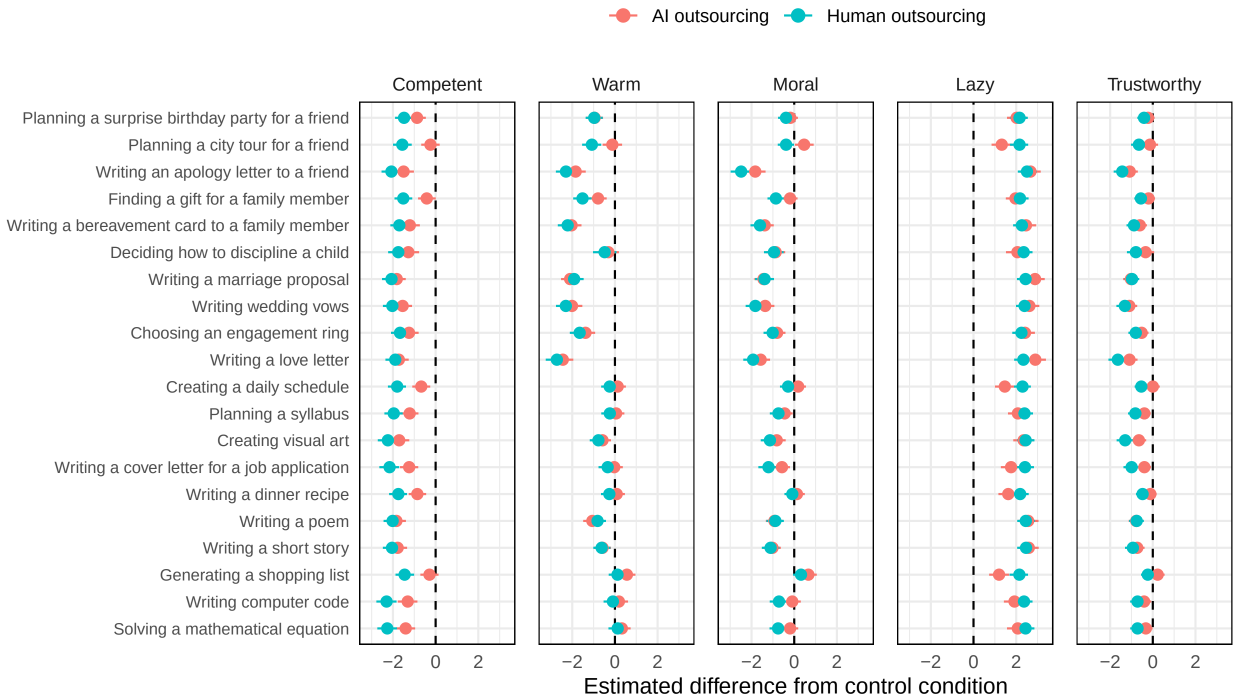
Supplementary Figure 20: Model-estimated means for the question “How important is it that others see the effort that goes into this task?” across all 20 tasks in the first pilot study. Grey points represent participant responses to the question, jittered for easier viewing. Black points are estimated means from the fitted model, pooling over participants. Black points and line ranges represent posterior medians and 95% credible intervals, respectively.



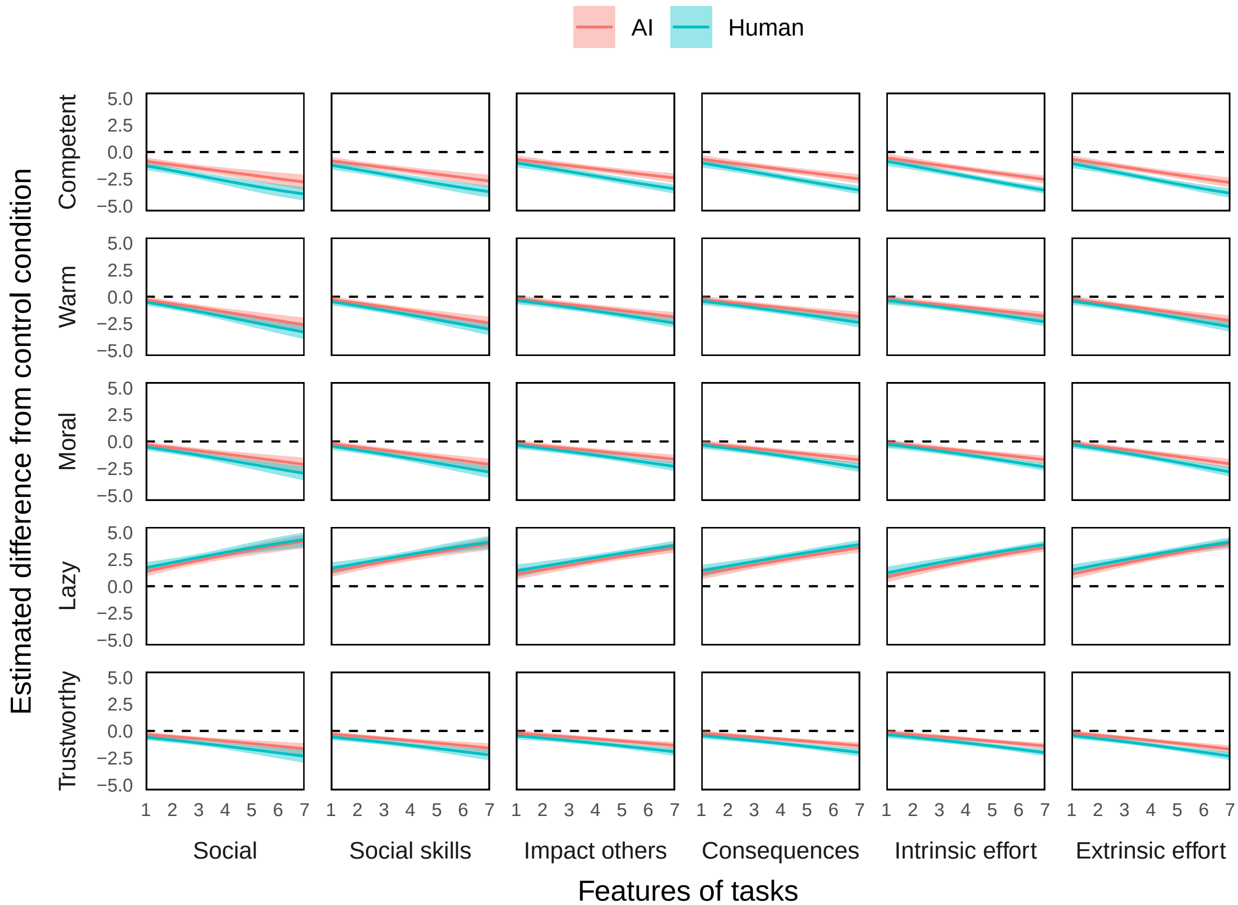
Supplementary Figure 21: Responses to the questions about ChatGPT in the second pilot study.



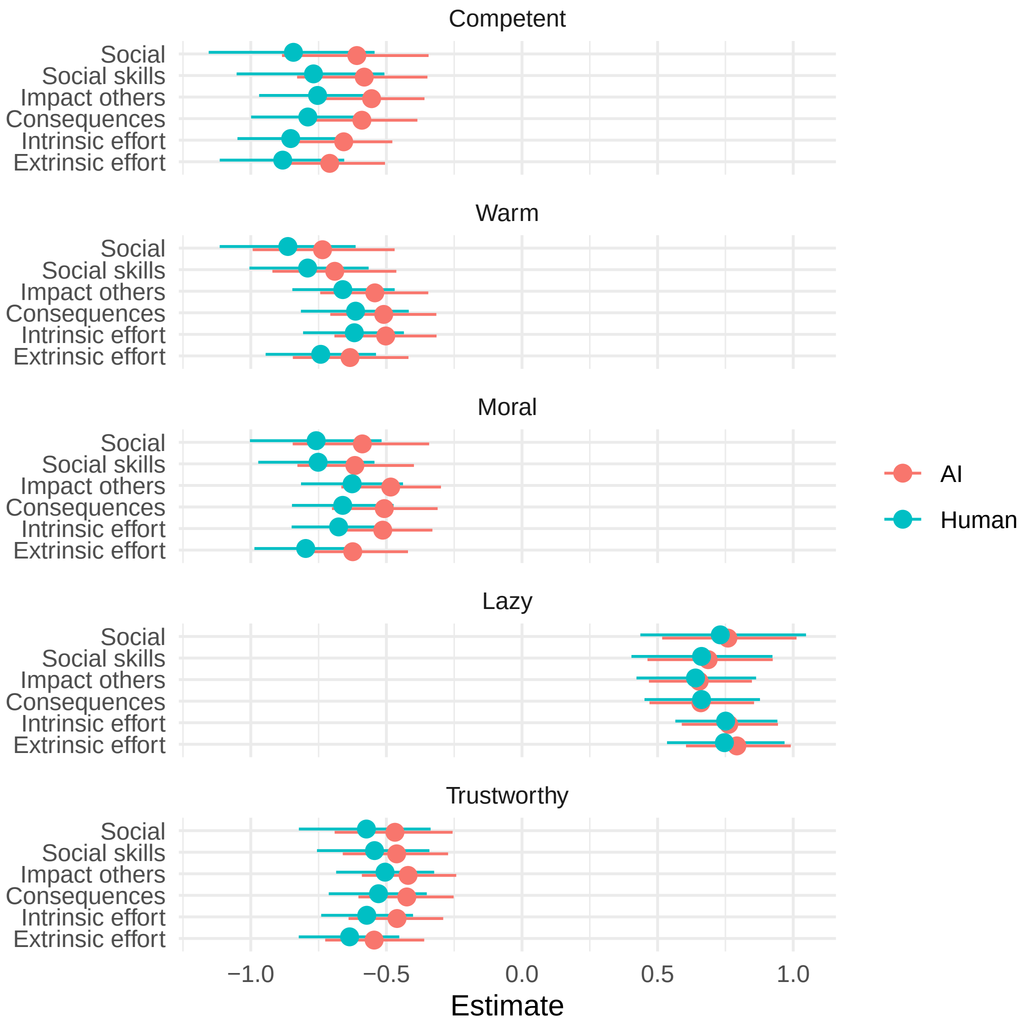
Supplementary Figure 22: Character evaluations in the second pilot study. Participants in the control condition, the AI outsourcing condition, and the human outsourcing condition evaluated people in the scenarios on (a) competence, (b) warmth, (c) morality, (d) laziness, and (e) trustworthiness. Coloured points represent participant responses to the questions, jittered for easier viewing. Black points are estimated marginal means from the fitted model, pooling over participants and tasks. Black points and line ranges represent posterior medians and 95% credible intervals, respectively.



Supplementary Figure 23: Variation in the effects of outsourcing across tasks in the second pilot study. Tasks are ordered from most social (top) to least social (bottom) according to ratings from the first pilot study. Point ranges are differences in marginal means on a 7-point Likert scale for the AI outsourcing condition (red) and the human outsourcing condition (blue) compared to the control condition. Points and ranges represent posterior medians and 95% credible intervals, respectively.



Supplementary Figure 24: The impact of task-specific features (e.g., being a social task) on the causal effects of outsourcing to AI (red) and humans (blue) compared to the control condition in the second pilot study. The y-axis reflects the estimated differences between the experimental conditions and the control condition (dashed line) on a 7-point Likert scale. Lines and shaded areas represent posterior medians and 95% credible intervals, respectively. The patterns indicate, for example, more negative effects of outsourcing on character evaluations for tasks that are rated as more social.



Supplementary Figure 25: Interaction parameters from models including task-specific features as moderators of the causal effects of AI outsourcing (red) and human outsourcing (blue) compared to the control condition in the second pilot study. Points and line ranges represent posterior medians and 95% credible intervals, respectively.

Supplementary Tables

Supplementary Table 1: Tasks included in the studies.

Task	Pilot Study 1	Pilot Study 2	Study 1	Study 2	Study 4
Writing wedding vows	✓	✓	✓	✓	✓
Writing a love letter	✓	✓	✓	✓	✓
Writing a marriage proposal	✓	✓	✓	✓	
Choosing an engagement ring	✓	✓	✓		
Finding a gift for a family member	✓	✓	✓		
Deciding how to discipline a child	✓	✓	✓		
Writing a bereavement card to a family member	✓	✓	✓	✓	✓
Writing an apology letter to a friend	✓	✓	✓	✓	✓
Planning a city tour for a friend	✓	✓	✓	✓	
Planning a surprise birthday party for a friend	✓	✓	✓	✓	
Writing a cover letter for a job application	✓	✓	✓	✓	✓
Writing computer code	✓	✓	✓	✓	✓
Solving a mathematical equation	✓	✓	✓	✓	✓
Planning a syllabus	✓	✓	✓	✓	✓
Writing a short story	✓	✓	✓	✓	
Writing a poem	✓	✓	✓	✓	
Creating visual art	✓	✓	✓		
Creating a daily schedule	✓	✓	✓	✓	
Generating a shopping list	✓	✓	✓	✓	
Writing a dinner recipe	✓	✓	✓	✓	

Supplementary Table 2: Pre-generated essay answers to the social prompt in Study 2.

Answer	Text
Father	My dad is one of the most important people in my life. He's always been someone I look up to and rely on. Throughout my whole life, he's been there to guide me, teach me, and support me in everything I do. What makes my dad special is how much he cares about our family. He works hard every day to make sure we have what we need, but no matter how busy he is, he always makes time for us. My dad is emotionally strong. Even though he doesn't show his emotions a lot, I can tell how much he cares by how much he does for us. When things get hard, he stays calm and steady, and that helps me feel better. One of my favorite things about my dad is how much he loves to teach. He knows so much and is always happy to share what he knows. He explains things in a way that makes sense and is easy to understand. I also love my dad's sense of humor. He always knows how to make me laugh with a joke or a funny story. His laughter makes everything feel lighter and happier. My dad has taught me so much about working hard, being kind, and staying strong when life is tough. I'm so thankful for everything he's done for me, and I'm proud to have him as my dad!
Sister	My sister is one of the most important people in my life. She is special because she always supports me. She has a way of making me feel confident, even when I'm unsure of myself. Whenever I'm scared to try something new, she's the first to remind me of what I can do. Her belief in me helps me believe in myself. My sister also has a really kind heart. She always thinks about others and does her best to help. She's always putting others first, whether it's being there for a friend or helping out with family. Her kindness is something I look up to and try to follow. Another thing I love about my sister is how funny she is. She has a great sense of humor and always knows how to make people laugh, even in serious moments. If I'm ever feeling down, she can cheer me up with a joke or a funny story. Her laughter makes everything feel lighter and happier. What I admire most about my sister is how strong she is. She's faced tough times but never lets them hold her back. Her strength gives me courage to keep going when life gets hard. My sister is more than just a family member — she's my role model and my rock!
Friend	My best friend is one of the most amazing people I know. She's someone I can count on no matter what. What makes her so special is her kindness. She always makes people feel important and cared for. Whether it's helping someone she just met or being there for her friends, she's the first to offer support. She never hesitates to help me, whether I'm upset or just having a bad day. She also has a great sense of humor that can cheer anyone up. She finds ways to laugh about even the smallest things, and her laugh is so contagious! Her laughter makes everything feel lighter and happier. What I admire most about her is how strong she is. Life hasn't always been easy for her, but she never gives up. She stays calm and keeps going, no matter what happens. Watching her face challenges in adulthood has taught me to be brave and not let hard times hold me back. My best friend has shown me what it means to be loyal, caring, and strong. I feel so lucky to have her in my life. I try to be as good of a friend to her as she is to me. She inspires me to be a better person!

Supplementary Table 3: Pre-generated essay answers to the non-social prompt in Study 2.

Answer	Text
The Hobbit	I will focus on describing the book “The Hobbit” by Tolkien. The Hobbit is a fantasy adventure story about Bilbo Baggins. Bilbo is a quiet hobbit who lives in the Shire. His life changes when Gandalf the wizard and a company of dwarves ask him to join their quest to take back treasure stolen by a dragon. At the beginning of the journey, Bilbo and the dwarves are nearly eaten by trolls, but Gandalf saves them. Then later, in the Misty Mountains, Bilbo meets a creature called Gollum and finds a magical ring that makes him invisible. This ring later becomes very important in “The Lord of the Rings”. As they travel, the group fights goblins, giant spiders in Mirkwood forest, and they get captured by Wood-elves. Bilbo shows his bravery by saving the group several times. Finally, they reach the Lonely Mountain where the dragon Smaug lives. Bilbo sneaks into the dragon’s lair and finds a weak spot in Smaug’s armor. The dragon gets angry and attacks the nearby town by a lake. Eventually, Smaug is killed. With the dragon dead, humans, elves, and dwarves all want the treasure. This leads to the “Battle of the Five Armies”. Tolkien doesn’t describe the battle in too much detail, but we later learn that the leader of the dwarves Thorin has fought bravely and died from his wounds. At the end of the story, Bilbo returns home to the Shire, richer and wiser from his adventure. He is happy to be back in his quiet life, and sets out to write a book of his adventures - which sets the stage for the sequel, The Lord of the Rings.
Buffy the Vampire Slayer	I will focus on describing the TV show “Buffy the Vampire Slayer”. Buffy is a TV show that completely flips the script on traditional high school dramas and supernatural horror. It’s about a teenager, Buffy Summers, who’s tasked with being the Slayer – basically a chosen one who hunts vampires and other demons. But what sets the show apart is how Buffy struggles to balance her responsibility with the regular teenage experience. She’s not just fighting creatures of the night, she’s also balancing school and friendships at the same time. One of the most striking things about Buffy is how layered the characters are. Buffy is tough and witty, but she’s also vulnerable. She’s faced with loss, guilt, and trying to make sense of her life outside of the supernatural chaos. And then there’s her team. Willow is the nerdy, sweet heart of the group, Xander is the funny loyal friend, and Giles (Buffy’s Watcher) is the stern mentor who’s also loving. Each character feels real, with their own flaws and growth arcs. The show has this incredible ability to mix humor, heart, and horror seamlessly. The dialogue is sharp and full of clever pop culture references. Yet, the writing isn’t afraid to get serious, exploring themes like trauma and growing up. The monsters Buffy faces often mirror real-life challenges, making the stakes feel personal. I love Buffy. It’s a show that’s smart and emotional, blending witty banter with moments of real depth. It’s got a cult following for a reason!
Titanic	I will focus on describing the film “Titanic”. The genre is a mix of romance, disaster, and historical tragedy. The film tells the love story of Jack and Rose, two passengers from different social classes aboard the passenger ship Titanic. Jack is a poor artist, but he manages to win a ticket to the ship’s maiden voyage. Rose is a young upper-class woman who is feeling trapped in her engagement to her fiance. Jack and Rose cross paths on the ship, and they fall in love. The film balances the spectacle of the ship’s design and atmosphere with the tension that gradually builds as the audience knows what fate awaits. The Titanic sails into the icy waters of the Atlantic and strikes an iceberg. Chaos immediately erupts. The film allows viewers to experience the terror, confusion, and heartbreak of the tragedy, showcasing both personal stories and the broader catastrophe. At its core, the film is a romance. But Titanic also touches on themes of class and fate. It highlights the disparity between the elite and the working-class passengers who are doomed to different fates. The film also explores the sense of inevitability that comes with knowing the ship’s doom. The most iconic scene from the film is arguably the scene where Jack and Rose stand together at the bow, arms outstretched. They seem free, but the scene also foreshadows the devastating crash to come. The film is truly heartbreaking!

Supplementary Table 4: Reading times and comprehension rates for the essay answers in Study 2. Expected reading times were calculated based on an estimated reading speed of 275 words per minute. Comprehension rates are the percentage of participants who answered the comprehension question correctly.

Prompt	Answer	Number of words	Expected reading time (secs)	Average reading time (secs)	Comprehension (%)
Social	Father	234	51.05	47.25	100.00
	Friend	211	46.04	49.91	98.50
	Sister	218	47.56	50.25	99.21
Non-social	Buffy	251	54.76	62.46	100.00
	Hobbit	278	60.65	65.97	99.28
	Titanic	239	52.15	63.90	100.00

Supplementary Table 5: Percentage of participants in Study 2 who passed the manipulation check and reported that they believed the manipulation, split by condition.

Condition	Pass manipulation check (%)	Believe manipulation (%)
Control	98.10	71.10
Tool outsourcing	96.11	77.99
Full outsourcing	100.00	86.07

Supplementary Table 6: Pairwise contrasts for character evaluations in Study 2. Numbers reflect differences in marginal means on a 7-point Likert scale. Estimates are pooled over essay answers. The bottom rows represent the interactions between outsourcing type and task type. Main numbers are posterior medians, numbers in the square brackets are 95% credible intervals.

	Response				
	Competent	Warm	Moral	Lazy	Trustworthy
Effect of outsourcing type					
Task type = Social					
Tool Social - Control Social	-0.97 [-1.33 -0.45]	-0.74 [-1.25 -0.12]	-0.81 [-1.16 -0.30]	1.31 [0.59 1.76]	-0.71 [-1.07 -0.21]
Full Social - Control Social	-0.99 [-1.96 -0.17]	-0.75 [-1.55 -0.03]	-0.78 [-1.63 -0.04]	0.87 [0.05 1.96]	-0.73 [-1.50 0.00]
Full Social - Tool Social	-0.03 [-1.13 0.92]	-0.03 [-1.06 0.92]	0.01 [-0.95 0.87]	-0.41 [-1.38 0.84]	-0.03 [-0.91 0.77]
Task type = Non-social					
Tool Non-social - Control Non-social	-1.21 [-1.55 -0.76]	-0.74 [-1.23 -0.10]	-0.91 [-1.28 -0.42]	1.82 [1.13 2.26]	-0.60 [-0.98 -0.17]
Full Non-social - Control Non-social	-1.48 [-2.41 -0.37]	-1.07 [-1.89 -0.11]	-1.15 [-2.11 -0.11]	1.48 [0.21 2.75]	-1.00 [-1.81 -0.04]
Full Non-social - Tool Non-social	-0.28 [-1.30 0.91]	-0.33 [-1.31 0.72]	-0.25 [-1.28 0.86]	-0.31 [-1.73 1.03]	-0.40 [-1.28 0.62]
Effect of task type					
Control Social - Control Non-social	-0.11 [-0.39 0.17]	0.57 [-0.16 0.99]	0.57 [0.15 0.88]	-0.24 [-0.55 0.11]	0.33 [-0.02 0.65]
Tool Social - Tool Non-social	0.13 [-0.30 0.61]	0.55 [-0.37 1.32]	0.66 [0.11 1.15]	-0.76 [-1.35 -0.15]	0.22 [-0.28 0.76]
Full Social - Full Non-social	0.34 [-0.37 1.07]	0.83 [-0.16 1.68]	0.92 [0.13 1.68]	-0.82 [-1.72 0.12]	0.56 [-0.14 1.27]
Interaction effect					
Interaction: Tool - Control	0.24 [-0.18 0.69]	-0.01 [-0.52 0.59]	0.10 [-0.32 0.57]	-0.52 [-1.06 0.00]	-0.11 [-0.53 0.38]
Interaction: Full - Control	0.46 [-0.21 1.13]	0.29 [-0.37 0.94]	0.35 [-0.33 1.05]	-0.57 [-1.41 0.28]	0.24 [-0.41 0.90]
Interaction: Full - Tool	0.21 [-0.60 1.02]	0.29 [-0.58 1.14]	0.25 [-0.53 1.09]	-0.06 [-1.03 0.99]	0.35 [-0.42 1.14]

Supplementary Table 7: Pairwise comparisons of word frequencies between conditions. LL = log likelihood.

Word	Control Freq.	Tool Freq.	Full Freq.	%DIFF Full vs Control	LL Full vs Control	%DIFF Tool vs Control	LL Tool vs Control	%DIFF Full vs Tool	LL Full vs Tool
Lazy	0	46	82	14138.18	97.16	6061.29	42.55	131.09	21.76
Genuine	36	11	12	-71.06	16.19	-79.54	25.91	41.42	0.69
Loves	9	9	0	-95.18	10.50	-33.03	0.72	-92.80	7.21
Romantic	0	7	0	-13.18	0.00	837.59	4.42	-90.74	5.16
Thoughtful	13	0	0	-96.66	16.27	-97.42	19.99	29.64	0.02
Caring	35	12	0	-98.76	49.01	-77.04	22.85	-94.60	10.36

Supplementary Table 8: Pairwise contrasts in the second pilot study. Numbers reflect differences in marginal means on a 7-point Likert scale, pooling over participants and tasks. Main numbers are posterior medians, numbers in the square brackets are 95% credible intervals.

	Response				
	Competent	Warm	Moral	Lazy	Trustworthy
AI - Control	-0.86 [-1.16 -0.55]	-0.30 [-0.57 -0.01]	-0.23 [-0.47 0.02]	1.80 [1.42 2.14]	-0.26 [-0.44 -0.05]
Human - Control	-1.68 [-1.98 -1.35]	-0.59 [-0.87 -0.28]	-0.54 [-0.80 -0.28]	2.26 [1.90 2.58]	-0.59 [-0.81 -0.39]
Human - AI	-0.81 [-1.15 -0.46]	-0.29 [-0.61 0.04]	-0.32 [-0.63 -0.02]	0.46 [0.04 0.90]	-0.33 [-0.58 -0.10]

Supplementary References

Boyd, R. L. (2019). BUTTER: Basic unit-transposable text experimentation resource. Available from https://www.butter.tools/

Gregson, R., Piazza, J., & Boyd, R. L. (2022). 'Against the cult of veganism': Unpacking the social psychology and ideology of anti-vegans. *Appetite*, *178*, 106143. doi:10.1016/j.appet.2022.106143

Rayson, P., & Garside, R. (2000). Comparing corpora using frequency profiling. *Proceedings of the Workshop on Comparing Corpora - Volume 9*, 1–6. Presented in Hong Kong. doi:10.3115/1117729.1117730