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# AI Aversion or Appreciation? A Capability–Personalization Framework and a Meta-Analytic Review

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Artificial intelligence (AI) is transforming human life. While some studies find that people prefer humans over AI (AI aversion), others find the opposite (AI appreciation). To reconcile these conflicting findings, we introduce the Capability–Personalization Framework. This theoretical framework posits that when deciding between AI and humans in a context, individuals focus on two dimensions: (a) perceived capability of AI and (b) perceived necessity for personalization. We propose that AI appreciation occurs when (a) AI is perceived as more capable than humans and (b) personalization is perceived as unnecessary in a given decision context, whereas AI aversion occurs when these conditions are not met. Our Capability–Personalization Framework is substantiated by a meta-analysis of 442 effect sizes from 163 studies ($N = 82{,}078$): AI appreciation occurs ($d = 0.27$, 95% CI [0.17, 0.37]) when AI is perceived as more capable than humans and personalization is perceived as unnecessary in a given decision context; otherwise, AI aversion occurs ($d = -0.50$, 95% CI [−0.63, −0.37]). Moderation analyses suggest that AI appreciation is more pronounced for tangible robots (vs. intangible algorithms), for attitudinal (vs. behavioral) outcomes, in between-subjects (vs. within-subjects) study designs, and in low unemployment countries, while AI aversion is more pronounced in countries with high levels of education and internet use. Overall, our integrative framework and meta-analysis advance knowledge about AI–human preferences and offer valuable implications for AI developers and users.

***Public Significance Statement***

To elucidate when people prefer AI over humans and vice versa, we introduce the Capability–Personalization Framework of AI aversion versus AI appreciation. Supporting this theoretical framework, our meta-analysis reveals that individuals tend to appreciate AI when it is perceived as more capable than humans and personalization is perceived as unnecessary in a given decision context; otherwise, AI aversion occurs. In other words, it is important to consider not only AI's capability but also its usage context. These insights empower developers and organizations to drive AI adoption and encourage individual users to embrace a more nuanced perspective on AI, ultimately facilitating AI integration into both professional and personal domains.

*Keywords:* artificial intelligence, AI aversion, AI appreciation, judgment and decision making, meta-analysis

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*continued*

Artificial intelligence (AI) refers to machines capable of performing cognitive functions commonly attributed to the human mind, such as learning, reasoning, and decision making. From physically intangible algorithms (e.g., medical diagnosis applications, *AlphaGo*) to tangible robots (e.g., service robots in restaurants, Boston Dynamics's *BigDog*), AI influences numerous aspects of daily life (Brynjolfsson & Mitchell, 2017; De Cremer et al., 2022; Glikson & Asscher, 2023; Glikson & Woolley, 2020; Hosny & Aerts, 2019; Qin et al., 2024; Sun et al., in press).

Despite AI's growing presence, some studies suggest that people tend to exhibit more negative attitudes and behaviors toward AI relative to humans, a phenomenon known as "AI aversion" (Cadario et al., 2021; Dietvorst et al., 2015; Longoni et al., 2019; Newman et al., 2020).[1,2] For example, in health care, patients are often less receptive to decisions made by medical AI compared to human doctors (Longoni et al., 2019). Similarly, in human resource (HR) management, job applicants tend to prefer personnel decisions made by human HR managers over those made by AI (Newman et al., 2020). Additionally, in moral domains such as law and the military, people are averse to AI-driven decisions even if the outcomes are favorable (e.g., a successful missile strike against terrorists that does not kill civilians; Bigman & Gray, 2018).

However, other studies suggest that people tend to exhibit more positive attitudes and behaviors toward AI relative to humans, a phenomenon known as "AI appreciation" (Logg et al., 2019; Marcinkowski et al., 2020). For example, Logg et al. (2019) find that controlling for advice quality, people tend to prefer advice provided by AI (vs. humans) for numeric estimation and forecasting tasks. Similarly, studies find that people perceive some standardized task-assignment processes (e.g., distributing pick lists) as fairer when executed by AI (vs. humans; B. Bai et al., 2022). Other studies find that people tend to trust AI's (vs. humans') advice more when guessing patterns in a card game (Sharan & Romano, 2020).

How can we reconcile these two seemingly contradictory research streams? In what contexts do people prefer AI over humans, and vice versa? Researchers from various disciplines have attempted to explain AI aversion or AI appreciation. Some macroeconomists argue that AI aversion stems from concerns about job displacement and economic inequality (Frey & Osborne, 2017; Korinek & Stiglitz, 2019); some philosophers surmise that AI aversion stems from concerns about privacy, transparency, and accountability (Müller, 2020); and some information scientists posit that AI appreciation stems from its potential to enhance human capabilities and productivity (Hou & Jung, 2021). Accordingly, recent reviews and meta-analyses in these disciplines have examined how AI relates to job displacement (Virgilio et al., 2024), economic inequality (Peppiatt, 2024), ethics (Corrêa et al., 2023), and productivity (Al Naqbi et al., 2024; Vaccaro et al., 2024). While these articles provide valuable insights, they have not directly examined individuals' attitudes toward AI. Although there are a few direct reviews of attitudes toward AI, they have focused on specific domains, such as health care (A. T. Young et al., 2021) and education (Chiu et al., 2023), without providing a unified theoretical framework that applies across domains, let alone reconciling the conflicting findings on AI aversion versus AI appreciation.

To address these knowledge gaps, we develop the Capability–Personalization Framework of AI aversion versus AI appreciation (depicted in Figure 1). Furthermore, we test our theoretical framework in a meta-analysis and explore potential moderators. Our research not only advances the theoretical understanding of AI aversion and AI appreciation, but also offers meaningful practical implications (e.g., guidelines for developers and organizations aiming to improve users' acceptance of AI).

## The Capability–Personalization Framework of AI Aversion Versus AI Appreciation

The Capability–Personalization Framework (Figure 1) posits that individuals focus on two key dimensions when deciding whether to rely on AI versus humans in a given decision context: (a) perceived capability of AI and (b) perceived necessity for personalization in the context. A core principle of attitude research, particularly emphasized in functional theories (Eagly & Chaiken, 1993; Katz, 1960), is that individuals' attitudes toward something are shaped by the extent to which they perceive it as serving their needs. In the context of AI, people's attitudes and behaviors toward AI—ranging from aversion to appreciation—depend on how well AI satisfies both utilitarian and psychological needs. Our Capability–Personalization Framework focuses on AI capability and personalization as two distinct dimensions because AI capability addresses the utilitarian need for task completion (Castelo et al., 2019; Puntoni et al., 2021), while personalization addresses the psychological need to be recognized as a unique individual (Longoni et al., 2019; Snyder & Fromkin,

[1] Dietvorst et al. (2015) seminal article used the phrase "*algorithm* aversion" instead of "*AI* aversion." Accordingly, Logg et al. (2019) influential article used the phrase "*algorithm* appreciation." To be comprehensive in our theorization and meta-analysis, we use the broader terms "*AI* aversion" and "*AI* appreciation."

[2] While Dietvorst et al. (2015) limited their definition to situations where individuals experience AI's errors, more recent research found that people show AI aversion even when AI does not err (Bigman & Gray, 2018; Longoni et al., 2019; Newman et al., 2020). Thus, our article uses a broader definition of AI aversion (De Freitas et al., 2023; Jussupow et al., 2020).

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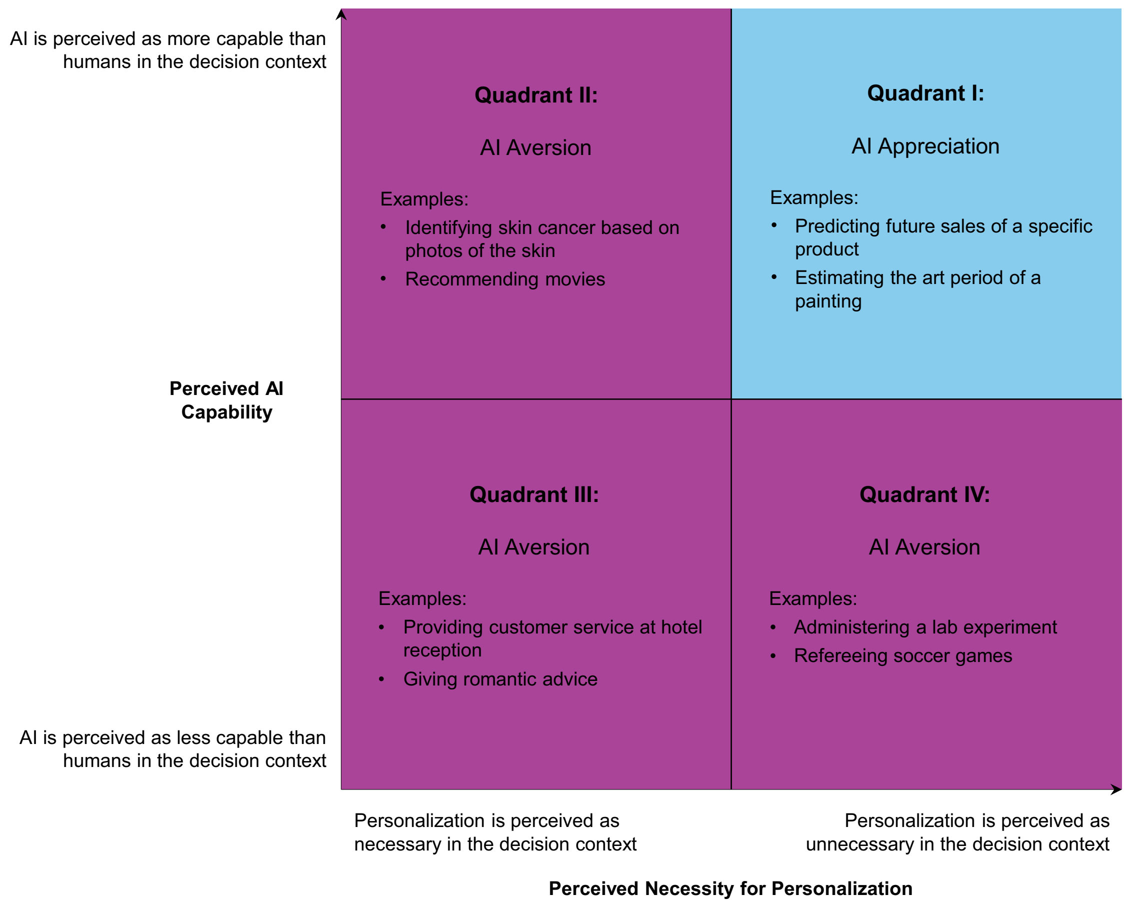
**Figure 1**

*Four Quadrants Based on the Capability–Personalization Framework of AI Aversion Versus AI Appreciation*




*Note*. AI = artificial intelligence. See the online article for the color version of this figure.



1980). Accordingly, we propose that AI appreciation occurs only when AI fulfills both utilitarian and psychological needs; otherwise, AI aversion occurs.

Regarding the first dimension, because individuals aim to complete tasks effectively and efficiently, they assess AI's capability in a given decision context: Is AI more capable than humans in this context? For example, AI is often perceived as more capable than humans in computational tasks (Balasubramanian et al., 2022; Jarrahi, 2018) and chess-related games (McIlroy-Young et al., 2020; Silver et al., 2018), but less capable than humans in tasks that involve morality, emotion, or creativity (Castelo et al., 2019; Fortuna & Modliński, 2021). When people perceive AI as less capable than humans in a decision context, they tend to be averse to AI's input. For example, Bigman and Gray (2018) found that people are averse to moral decisions made by AI because they perceive AI as less capable than humans in moral contexts, but this aversion is mitigated when AI's perceived capability is increased.

However, high perceived capability alone does not guarantee AI appreciation, because whether individuals prefer AI or humans also hinges on the second dimension: the extent to which personalization is perceived as necessary in the decision context.[3] Human beings have the fundamental desire to view themselves as distinct from others (e.g., Snyder & Fromkin, 1980). Meanwhile, AI is viewed as operating in a standardized, rote manner (Haslam, 2006). Thus, even if AI's capability is high, people may doubt whether AI can sufficiently consider their personalized needs and circumstances (Longoni et al., 2019; Newman et al., 2020; Yokoi et al., 2021). Therefore, in decision contexts where personalization is perceived as necessary, AI aversion tends to occur. For example, Longoni et al. (2019) consistently found that "participants were resistant to medical AI even when the performance of AI providers was explicitly specified to be superior to that of human providers" (p. 636) because "the prospect of being cared for by AI providers is more likely to evoke a concern that one's unique characteristics, circumstances, and symptoms will be neglected" (p. 630). As a concrete example, consider triage diagnoses, where the accuracy rate of AI (90.2%) was found to be higher than that of human doctors (77.5%; Donnelly, 2017). Yet, Longoni et al. (2019, Study 3B) found that even when AI's capability was explicitly specified to be superior, patients still preferred human

[3] Notably, the "personalization" dimension of our framework is a decision context characteristic rather than an AI characteristic. That is, this dimension does not concern AI's ability to tailor its responses to different individuals; rather, this dimension concerns the extent to which people's personalized needs and circumstances should be considered in a given decision context.

nurses due to the high perceived necessity for personalization in the context of triage diagnoses. Similarly, research suggests that employees perceive HR decisions made by AI as less fair than those made by humans—even when the outcomes are identical—because they believe that personalization is necessary in the HR context (Newman et al., 2020).

Importantly, the two dimensions—(a) perceived capability of AI and (b) perceived necessity for personalization in the decision context—are theoretically distinct for two reasons. The first reason is that individuals may perceive personalization as necessary in a decision context regardless of their perceptions of AI's capability. For example, even if job applicants perceive AI as superior to humans in selecting the right candidates, applicants may still perceive it as necessary to consider personalization and thus prefer to be screened by human recruiters. Therefore, perceived capability alone (i.e., a one-dimensional framework) cannot sufficiently explain when AI aversion versus AI appreciation occurs. The second reason is that, even within the same context, different focal parties may have different perceptions of whether it is necessary to consider personalization. For example, in job recruitment, even if applicants and recruiters agree on AI's capability, they may differ in perceived necessity for personalization. Whereas an applicant may feel unique and believe that only human recruiters can understand their individual needs and circumstances, a recruiter who has interviewed numerous applicants may think that applicants can be assessed effectively by AI using standardized criteria. In other words, for a given decision context, the perceived necessity for personalization can vary among the focal parties due to differing stakes and perspectives.

In summary, our Capability–Personalization Framework posits that AI appreciation occurs only when AI is perceived as more capable than humans, and personalization is perceived as unnecessary in a given decision context (i.e., Quadrant I in Figure 1). For example, in tasks like predicting future sales of a product or estimating the art period of a painting, AI is perceived as more capable than humans and personalization is perceived as unnecessary (Logg et al., 2019), so AI appreciation occurs. In the other three conditions—Quadrant II (AI capability is superior and necessity for personalization is high), Quadrant III (AI capability is inferior and necessity for personalization is high), and Quadrant IV (AI capability is inferior and necessity for personalization is low) in Figure 1—AI aversion occurs. For example, in hotel reception services, AI is perceived as less capable than humans (Choi & Wan, 2021), so AI aversion occurs. In contrast, while AI may be perceived as more capable than radiologists in identifying skin cancer from photos because it is trained on large data sets (H. X. Bai et al., 2020; Hosny et al., 2018), AI aversion still occurs because of the high perceived necessity for personalization in this context.

# Method

## Transparency and Openness

To provide a systematic test of our Capability–Personalization Framework, we conducted a meta-analysis. We adhered to the standard reporting guidelines outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 statement (Page et al., 2021). All data and code are publicly available at https://osf.io/8skz6/ (Qin et al., 2025).

## Literature Search

We implemented several steps to obtain studies from electronic databases (Web of Science Core Collection, APA PsycInfo, IEEE Xplore, ACM Digital, and Engineering Village) and other sources (Google Scholar, within-article citation search, and public calls for unpublished studies) in July 2022. First, we searched electronic databases using a combination of AI-related keywords ("artificial intelligence" OR "AI" OR "A.I." OR "algorithm" OR "robot" OR "autonomous vehicle" OR "machine learning"), human-related keywords ("human" OR "human being" OR "people" OR "person" OR "individual"), comparison-related keywords ("compare" OR "comparison" OR "contrast" OR "vs." OR "versus"), and preference-related keywords ("prefer" OR "trust" OR "fair"). Second, in Google Scholar, one author conducted searches of 5 (AI–human comparison: "artificial intelligence vs. human," "algorithm vs. human," "robot vs. human," "autonomous vehicle vs. human," and "machine learning vs. human") × 3 (preference for human or AI: "prefer," "trust," and "fair") keyword combinations (e.g., "artificial intelligence vs. human" and "prefer"). To be comprehensive, this author reviewed the first 100 Google Scholar results for each keyword combination. Since Google Scholar automatically colors articles that have been viewed, duplicate articles were naturally excluded. Based on abstracts, this author then excluded articles that did not compare AI and humans. Third, three other authors searched for additional studies via a within-article citation search by reviewing the reference sections of each article. Fourth, we issued calls for unpublished studies through LISTSERVs and research forums (e.g., the Academy of Management, the Society for Personality and Social Psychology).

## Inclusion Criteria

We limited our meta-analysis to articles that (a) were written in English, (b) provided relevant data for us to calculate effect sizes, and (c) empirically tested preference for AI versus humans. For inclusion criterion (c), we only included studies that directly compared AI and humans, and we excluded studies that solely focused on AI; for example, we excluded studies that investigated how AI characteristics (e.g., autonomy) influence people's preference for AI—without comparing AI to humans (e.g., Chao et al., 2016). In addition, among the between-subjects studies, we excluded studies that did not specify experimental conditions (AI or humans; e.g., a study in which participants rated a text without being informed whether it was generated by human journalists or algorithms; Clerwall, 2014).

## Coding Decision Contexts

In light of the Capability–Personalization Framework, we assessed (a) perceived capability of AI (vs. humans) in a decision context and (b) perceived necessity for personalization in a decision context.[4]

[4] For the quadrant-by-quadrant analyses, we excluded 13 studies where participants were asked to experience multiple decision contexts because we were unable to categorize such studies into one quadrant. For example, our quadrant-by-quadrant analyses excluded Castelo et al. (2019) Study 1, which calculated preference for AI (vs. humans) by averaging across 26 decision contexts, including disease treatment recommendation (where perceived necessity for personalization is high) and stock prediction (where perceived necessity for personalization is low).

To assess perceived AI capability in a decision context, we used the following item: "When making a decision in this context, how capable is AI compared to humans?" (1 = "far less capable," 6 = "far more capable"). To assess perceived necessity for personalization in a decision context, we used the following item: "When making a decision in this context, is personalization necessary for the focal party?" (1 = "highly unnecessary," 6 = "highly necessary"). For example, in the context where the goal was to estimate the weight of someone in a photo (Logg et al., 2019), coders generally rated AI as more capable than humans, yielding a high rating for perceived capability of AI (vs. humans). Meanwhile, coders generally perceived it as unnecessary to consider personalization in this context, yielding a low rating for perceived necessity for personalization.

Using these two items, 13 coders independently rated a total of 93 decision contexts (randomly ordered) from the studies. The average interrater agreement (James et al., 1984) was high for both perceived AI capability (mean $r_{wg}$ = .89, median $r_{wg}$ = .89) and perceived necessity for personalization (mean $r_{wg}$ = .86, median $r_{wg}$ = .86). Hence, for each decision context, we averaged the coder ratings to calculate (a) perceived capability of AI and (b) perceived necessity for personalization. Based on the scale midpoint of 3.5 for the two items, we then categorized these decision contexts into Figure 1's four quadrants (i.e., Quadrant I: AI capability > 3.5 and personalization < 3.5; Quadrant II: AI capability > 3.5 and personalization > 3.5; Quadrant III: AI capability < 3.5 and personalization > 3.5; Quadrant IV: AI capability < 3.5 and personalization < 3.5).

## Moderators

To examine the heterogeneity in effect sizes, we tested a broad set of potential moderators in metaregressions: (a) AI characteristics (tangible robot vs. intangible algorithm), (b) study characteristics (behavioral vs. attitudinal measures of preference, between-subjects vs. within-subjects designs, study quality, effect size conversion), (c) sample characteristics (female percentage, crowdsourced vs. other samples), (d) publication characteristics (publication status, publication year), and (e) country/territory characteristics[5] (unemployment rate, gross domestic product (GDP) per capita, college degree percentage, internet use percentage). For the definition and data source of each variable, see Supplemental Table S1.

## Statistical Procedures

Following standard meta-analytic guidelines (Hunter & Schmidt, 2004; Morris & DeShon, 2002), we converted all effect sizes (e.g., correlation, *t* statistics) to Cohen's *d* values.[6] Out of the 442 effect sizes, 77 (17.4%) were converted. Positive *d* values indicate that participants prefer AI over humans (i.e., AI appreciation), whereas negative *d* values indicate that participants prefer humans over AI (i.e., AI aversion).

Because some studies used a between-subjects design and others used a within-subjects design, we applied Morris and DeShon's (2002) aggregation procedures to combine effect sizes across the two designs. We used the inverse of the sampling variance as the weight for each effect size, a common meta-analytic approach that assigns greater weight to studies with smaller sampling variance (i.e., more precise estimates; Hedges & Olkin, 1985; Morris & DeShon, 2002).

Some studies reported multiple effect sizes, so we accounted for such statistical dependency by adjusting the calculations of *SE*s and weights of the studies (Konstantopoulos, 2011). Specifically, we used robust variance estimation (Hedges et al., 2010) in the R package *metafor* (Viechtbauer, 2010), which has been used in many meta-analyses (e.g., Agadullina & Lovakov, 2018; Bediou et al., 2018; Friese et al., 2017; Kurdi et al., 2019).

We used the random-effects approach of meta-analysis. Compared with a fixed-effects approach, a random-effects approach "is more conservative and appropriate when the goal is to generalize beyond the available studies without assuming that there is only one true, 'fixed' effect size" (Lu et al., 2020, p. 749). Data were analyzed using R (Version 4.3.1) and the package *metafor* (Version 3.0-2; Viechtbauer, 2010).

To better interpret the moderation results, we adopted the moving constant technique developed by Johnson and Huedo-Medina (2011). Increasingly used in meta-analyses (e.g., Bediou et al., 2018; Johnson & Hennessy, 2019; Knittle et al., 2018), the moving constant technique "relies on meta-regression models to create graphs or tables of estimated mean effect sizes plotted against moderator values, including confidence intervals or confidence bands" (Johnson, 2021, p. 7). We used this technique to estimate weighted mean effect sizes and their confidence intervals at different levels of study- and country-level moderators while statistically holding other moderators constant at their mean levels.

# Results

## Study Characteristics

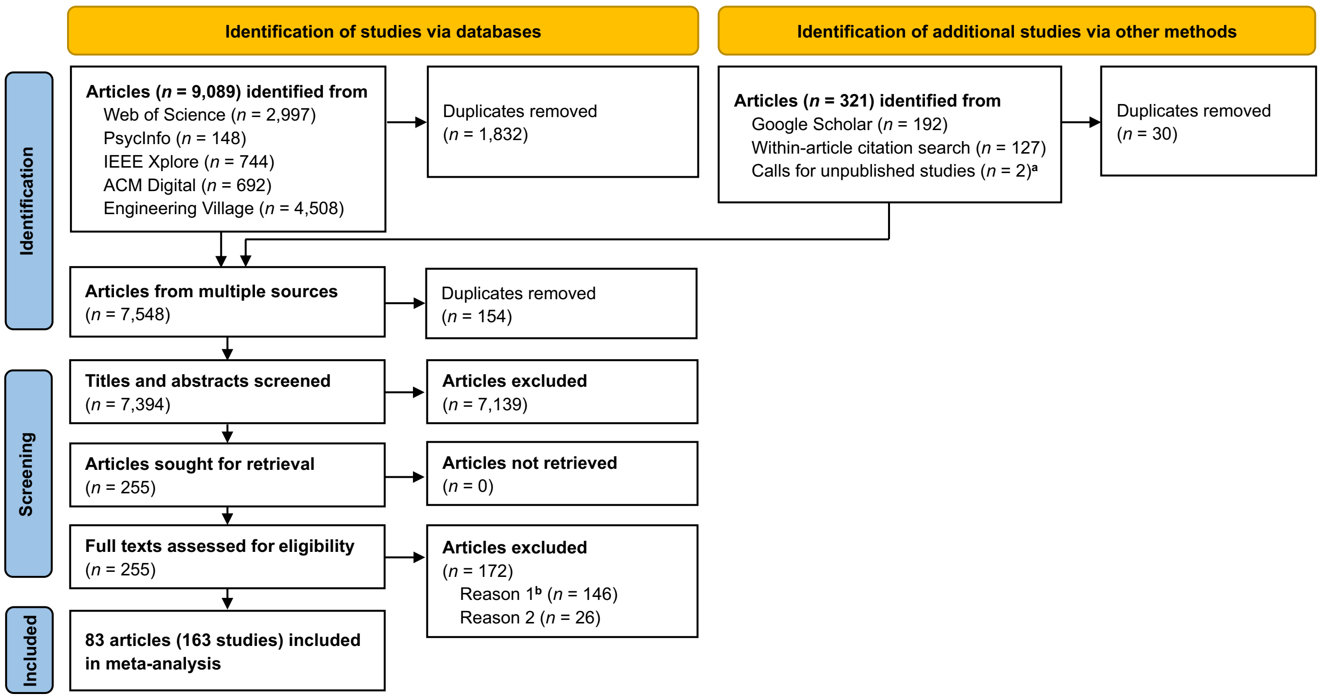
The Preferred Reporting Items for Systematic Reviews and Meta-Analyses flow diagram showing the article selection process for the meta-analysis is displayed in Figure 2. Our literature search yielded 9,089 articles from electronic databases and 321 articles from other methods. After removing duplicates and excluding ineligible articles based on abstracts (e.g., studies that did not compare AI and humans), we retained 255 articles for full-text eligibility assessment. After careful screening, we excluded 172 articles that did not meet our inclusion criteria. Ultimately, our meta-analysis included 83 articles (see Supplemental Table S2), yielding 442 effect sizes from 163 studies (*N* = 82,078).

Table 1 presents a summary of the descriptive statistics for the 442 effect sizes. Specifically, the majority of studies examined intangible algorithms (92.8%) rather than tangible robots, examined attitudinal outcomes (92.5%) rather than behavioral outcomes, and used a between-subjects design (84.8%) rather than a within-subjects design. Across the studies, the mean female percentage was 56.1%, and 49.1% of these studies used crowdsourced samples. The majority of studies were published (88.5%), and the mode publication year was 2021.

[5] For simplicity, we use "country" to denote "country/territory" in the rest of the article.

[6] An effect size is considered converted if it was derived from *F*, *t*, *r*, or chi-squared statistics, whereas an effect size is considered not converted if it was directly sourced from the article or calculated from mean and standard deviation.

**Figure 2**
*PRISMA Flow Diagram Showing the Process of Obtaining 83 Articles (163 Studies) for the Meta-Analysis*




*Note.* PRISMA = Preferred Reporting Items for Systematic Reviews and Meta-Analyses. See the online article for the color version of this figure. [a] Studies we received after issuing calls via LISTSERVs and research forums. [b] Reason 1 refers to the absence of empirical testing of preference for artificial intelligence versus humans. Reason 2 refers to insufficient data reported for calculating effect sizes.

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## Testing the Capability–Personalization Framework of AI Aversion Versus AI Appreciation

The distribution of effect sizes is presented in Figure 3; larger positive values indicate a greater preference for AI over humans. Our meta-analysis of 442 effect sizes from 163 studies ($N = 82{,}078$) found that, at first glance, people prefer humans over AI, Cohen's $d = -0.26$, 95% CI [−0.37, −0.15], $t(441) = -4.81$, $p < .001$, but this effect is small according to conventional criteria for Cohen's $d$ (Cohen, 1988).

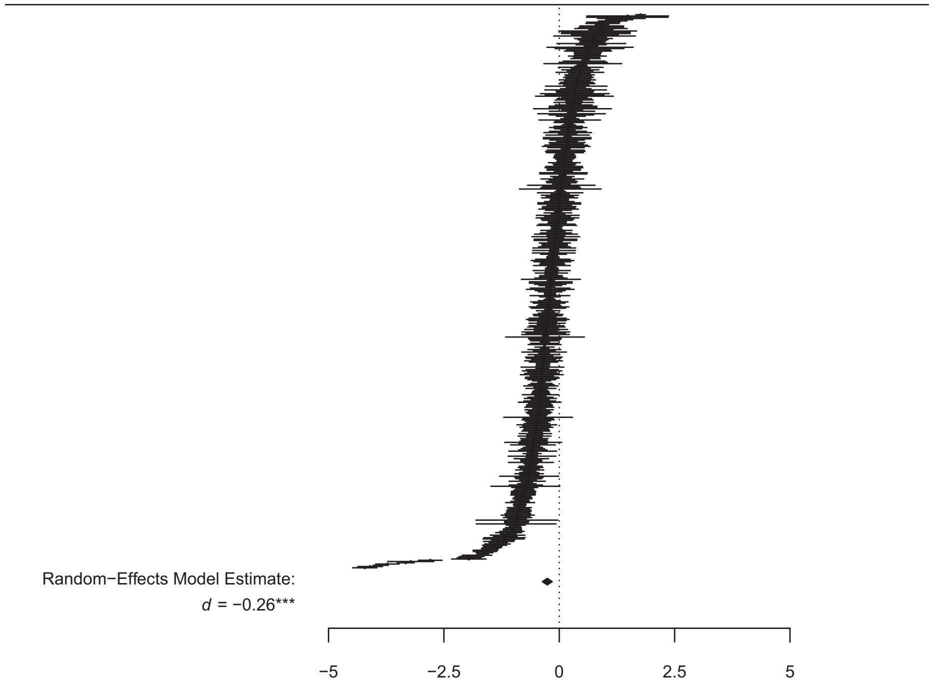
Importantly, a test for heterogeneity revealed substantial variability in the effect sizes, $Q(441) = 15350.05$, $p < .001$; $I^2 = 97.96\%$. Although the overall effect size is $d = -0.26$, the 80% prediction interval (which denotes where 80% of future values are

**Table 1**
*Descriptive Statistics*

| Variable | Frequency or *M* (*SD*) | Median | Mode (statistical) | Range | *n* | *k* |
|---|---|---|---|---|---|---|
| AI characteristics | | | | | | |
| Tangible robot versus intangible algorithm | 7.2% tangible robot | | Intangible algorithms | 0 or 1 | 161 | 432 |
| Study characteristics | | | | | | |
| Behavioral versus attitudinal outcomes | 7.5% behavior | | Attitude | 0 or 1 | 163 | 442 |
| Between-subjects versus within-subjects designs | 84.8% between-subjects | | Between-subjects | 0 or 1 | 163 | 442 |
| Study quality | −0.03 (0.69) | −0.21 | −0.71 | −0.71 to 1.50 | 163 | 442 |
| Effect size conversion | 17.4% converted | | No conversion | 0 or 1 | 163 | 442 |
| Sample characteristics | | | | | | |
| Female percentage | 0.56 (0.13) | 0.53 | 0.53 | 0–1 | 146 | 400 |
| Crowdsourced versus other samples | 49.1% crowdsourced | | Other sample | 0 or 1 | 163 | 442 |
| Publication characteristics | | | | | | |
| Published versus not | 88.5% published | | Published | 0 or 1 | 163 | 442 |
| Publication year | 2018.37 (4.97) | 2020 | 2021 | 2000–2022 | 163 | 442 |
| Country characteristics | | | | | | |
| Unemployment rate | 0.06 (0.01) | 0.06 | 0.06 | 0.04–0.10 | 146 | 402 |
| GDP per capita (log) | 10.63 (0.37) | 10.72 | 10.72 | 8.33–11.08 | 146 | 402 |
| College degree percentage | 0.23 (0.07) | 0.28 | 0.28 | 0.02–0.28 | 146 | 402 |
| Internet use percentage | 0.57 (0.05) | 0.57 | 50.57 | 0.25–0.64 | 146 | 402 |
| Sample size | 332.33 (1979.99) | 185 | 74 | 11–41,592 | 163 | 442 |

*Note.* $n$ = number of studies; $k$ = number of effect sizes; AI = artificial intelligence; GDP = gross domestic product.

**Figure 3**
*Forest Plot of All Effect Sizes (k = 442) Included in the Random-Effects Meta-Analysis*




*Note*. Positive effect sizes indicate that participants prefer AI over humans (i.e., AI appreciation), whereas negative effect sizes indicate that participants prefer humans over AI (i.e., AI aversion). AI = artificial intelligence.

expected to fall) ranges from −1.13 to 0.61, indicating that people's preference for AI can vary widely, from large negative to positive effect sizes. Thus, we further compared Quadrant I with each of the other three quadrants based on our Capability–Personalization Framework (Figure 1).[7] A metaregression found that the mean effect size of Quadrant I is significantly more positive than the mean effect sizes of the other three quadrants (Table 2: all $p$s $< .001$).

Next, we meta-analyzed the effect sizes in each quadrant separately (Table 3). We chose to analyze by quadrant instead of testing the interactive effect of perceived AI capability and personalization because whether the Capability–Personalization Framework is supported does not equate to whether the interactive effect of perceived AI capability and personalization is significant. For a detailed explanation and illustrations, see Supplemental Figure S1a and S1b.

Quadrant I (high AI capability and low personalization) has a mean effect size of $d = 0.27$, $k_{\text{sample}} = 46$, $k_{\text{es}} = 106$, 95% CI [0.17, 0.37], $t(105) = 5.23$, $p < .001$. This result indicates that in decision contexts characterized by high AI capability and low personalization, people prefer AI over humans. By contrast, Quadrant II (high AI capability and high personalization) has a mean effect size of $d = -0.43$, $k_{\text{sample}} = 14$, $k_{\text{es}} = 27$, 95% CI [−0.54, −0.32], $t(26) = -7.55$, $p < .001$, Quadrant III (low AI capability and high personalization) has a mean effect size of $d = -0.38$, $k_{\text{sample}} = 53$, $k_{\text{es}} = 184$, 95% CI [−0.53, −0.23], $t(183) = -5.03$, $p < .001$, and Quadrant IV (low AI capability and low personalization) has a mean effect size of $d = -0.69$, $k_{\text{sample}} = 37$, $k_{\text{es}} = 97$, 95% CI [−0.98, −0.39], $t(96) = -4.60$, $p < .001$. When combined, Quadrants II, III, and IV have a mean effect size of $d = -0.50$, $k_{\text{sample}} = 104$, $k_{\text{es}} = 308$,

**Table 2**
*Metaregression of Preference for AI (vs. Humans)*

| Variable | *b* | *SE* | *t* | *p* |
|---|---|---|---|---|
| Intercept = Quadrant I (high AI capability and low personalization) [reference group] | 0.27 | 0.09 | 3.01 | .003 |
| Quadrant II (high AI capability and high personalization) | −0.72 | 0.18 | −3.90 | <.001 |
| Quadrant III (low AI capability and high personalization) | −0.65 | 0.12 | −5.37 | <.001 |
| Quadrant IV (low AI capability and low personalization) | −0.96 | 0.13 | −7.17 | <.001 |

*Note*. Negative *b* values indicate that the mean effect sizes of Quadrants II, III, and IV are less positive than the mean effect size of Quadrant I, which means that participants in Quadrants II, III, and IV are less likely to prefer AI over humans than participants in Quadrant I. *b* = coefficient in the metaregression; *SE* = standard error; AI = artificial intelligence.

[7] Regarding effect sizes, Cohen (1988) considers $|r| = .10$ to .29 as small, $|r| = .30$ to .49 as medium, $|r| > .50$ as large (Jané et al., 2024). In support of the two dimensions being theoretically distinct, our meta-analysis found that the two dimensions are only weakly correlated at $r = -.29$. Notably, many construct pairs that are considered theoretically distinct have similar or even higher correlations (in magnitude), such as warmth and competence ($r = .71$; Leslie et al., 2014), intrinsic and extrinsic motivation ($r = -.24$; Lepper et al., 2005), and divergent and convergent thinking ($r = .31$; Lu et al., 2017).

**Table 3**
*Meta-Analysis of Preference for AI (vs. Humans) in Each of the Four Quadrants*

| Condition | $k_{sample}$ | $k_{es}$ | $N$ | $d$ | $SD$ | 95% CI | 80% prediction interval | $I^2$ |
|---|---|---|---|---|---|---|---|---|
| Quadrant I (high AI capability and low personalization) | 46 | 106 | 8,784 | 0.27 | 0.31 | [0.17, 0.37] | [−0.14, 0.67] | 90.82% |
| Quadrant II (high AI capability and high personalization) | 14 | 27 | 3,400 | −0.43 | 0.18 | [−0.54, −0.32] | [−0.67, −0.19] | 66.02% |
| Quadrant III (low AI capability and high personalization) | 53 | 184 | 15,853 | −0.38 | 0.54 | [−0.53, −0.23] | [−1.09, 0.32] | 96.10% |
| Quadrant IV (low AI capability and low personalization) | 37 | 97 | 9,805 | −0.69 | 0.90 | [−0.98, −0.39] | [−1.86, 0.48] | 98.19% |

*Note*. Positive $d$ values indicate that participants prefer AI over humans (i.e., AI appreciation), whereas negative $d$ values indicate that participants prefer humans over AI (i.e., AI aversion). $k_{sample}$ = number of samples; $k_{es}$ = number of effect sizes; $N$ = number of participants; $d$ = Cohen's $d$; $SD$ = standard deviation of Cohen's $d$; CI = confidence interval; $I^2$ = percentage of the total variability due to heterogeneity; $b$ = coefficient in the metaregression; $SE$ = standard error; AI = artificial intelligence.



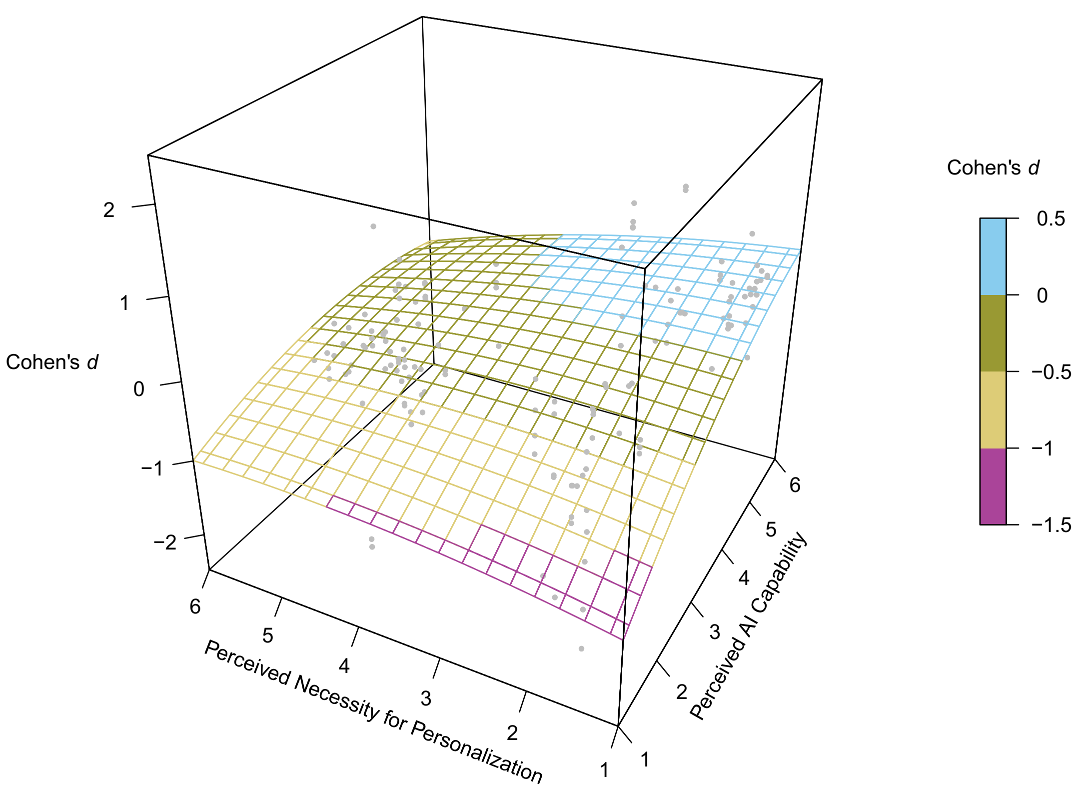
95% CI [−0.63, −0.37], $t(307) = -7.36$, $p < .001$, indicating that people show AI aversion in these decision contexts.

A 3D figure (Figure 4) visualizing the full distribution of effect sizes as a function of the two dimensions of the Capability–Personalization Framework further supports the framework: AI appreciation occurs (cyan area) only when AI is perceived as more capable than humans and personalization is perceived as unnecessary in a given decision context; otherwise, AI aversion occurs (purple/sand/olive area). To illustrate the effect sizes from different angles, we also provide four more 3D figures in Supplemental Materials (see Supplemental Figure S2a–S2d).

## Robustness Checks

To ascertain the reliability of our findings, we conducted various robustness checks. First, we categorized decision contexts into four

**Figure 4**
*Scatterplot Visualizing AI Aversion Versus AI Appreciation as a Function of Perceived AI Capability and Perceived Necessity for Personalization*




*Note*. Positive $d$ values indicate that participants prefer AI over humans (i.e., AI appreciation), whereas negative $d$ values indicate that participants prefer humans over AI (i.e., AI aversion). The figure illustrates that AI appreciation occurs (cyan area) only when AI is perceived as more capable than humans and personalization is perceived as unnecessary in a given decision context; otherwise, AI aversion occurs (purple/sand/olive area). The editorial team noted that since most effect sizes fall within the range of −2.5 to 2.5, it might be excessively precise to present a range of −4 to 4 for the effect sizes. To facilitate visualization, the plot only presents the effect sizes within the range of −2.5 to 2.5 and excludes those outside this range. AI = artificial intelligence. See the online article for the color version of this figure.

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quadrants using the median value of the AI capability and personalization dimensions, rather than the scale midpoint of 3.5. All results remained robust under this alternative categorization (see Supplemental Tables S3 and S4 for more details).

Second, outlier analyses—using metrics including Cook's distance (Cook & Weisberg, 1982; Hedges & Olkin, 1985) and DFBETA values—identified no outliers in Quadrants I and II, three outliers in Quadrant III, and five outliers in Quadrant IV. Results remained robust after removing these eight outliers (see Supplemental Tables S5 and S6 and Supplemental Figure S3a–S3e for more details).

Third, following the literature (Simonsohn et al., 2022), we repeated the meta-analyses for high-quality studies only. Following previous meta-analyses (Dai et al., 2023; Donald et al., 2021; Macnamara & Burgoyne, 2023), we assessed study quality based on four indicators: (a) whether a study conducted a power analysis, (b) whether a study reported preregistration, (c) whether a study reported participant exclusions from analyses, and (d) whether a study included attention checks. Results remained robust when we reran the meta-analyses after excluding studies that scored below the median on the quality assessment (see Supplemental Tables S7 and S8 for more details).

## Moderator Analyses

In accordance with the Capability–Personalization Framework, we conducted one set of moderator analyses for Quadrant I (high AI capability and low personalization; Table 4) and a separate set of moderator analyses for the other three quadrants (Table 5). Tables 4 and 5 present the results of metaregressions: Model 1 includes all study-level variables, and Model 2 adds country-level variables.

### *AI Characteristics*

Research suggests that people tend to prefer tangible AI over intangible AI because physical embodiment increases AI's perceived social presence (Kiesler et al., 2008). For example, the physical embodiment of AI can foster trust in AI (Glikson & Woolley, 2020). Thus, one moderator we tested was whether the AI is a tangible robot or an intangible algorithm. Metaregressions found that when AI is a tangible robot (vs. intangible algorithm), AI appreciation is more pronounced in Quadrant I (Table 4, Figure 5a). Meanwhile, AI embodiment (tangible robot vs. intangible algorithm) is not a significant moderator in the other three quadrants (Table 5).

### *Study Characteristics*

In terms of study characteristics, we investigate (a) behavioral versus attitudinal measures of preference, (b) between-subjects versus within-subjects designs, (c) study quality, and (d) effect size conversion.

**Behavioral Versus Attitudinal Outcomes.** Research suggests that although individuals may exhibit strong attitudes toward something (e.g., due to initial gut feelings), their actual behaviors may be more reserved (Bezrukova et al., 2016; Glasman & Albarracín, 2006; Roesler et al., 2021). For example, some patients may express attitudinal aversion to medical AI, but such aversion may weaken when it comes to actual AI adoption for their medical treatment. A study found that, on average, the benefits of robot anthropomorphism are more pronounced for attitudinal than behavioral outcomes (Roesler et al., 2021). Thus, another moderator we tested was whether a study involved behavioral outcomes, such as advice utilization (Longoni et al., 2019; Prahl & Van Swol, 2017) and

**Table 4**
*Quadrant I Moderator Analyses: Metaregressions*

| Tested moderator | Model 1 | | | | Model 2 | | | |
|---|---|---|---|---|---|---|---|---|
| | *b* | *SE* | *p* | 95% CI | *b* | *SE* | *p* | 95% CI |
| AI characteristics | | | | | | | | |
| Tangible robot versus intangible algorithm | 0.53 | 0.20 | .0095** | [0.13, 0.93] | 0.43 | 0.20 | .03* | [0.05, 0.82] |
| Study characteristics | | | | | | | | |
| Behavioral versus attitudinal outcomes | −0.15 | 0.06 | .0098** | [−0.27, −0.04] | −0.11 | 0.06 | .06 | [−0.23, 0.01] |
| Between-subjects versus within-subjects designs | 0.35 | 0.13 | .009** | [0.09, 0.61] | 0.26 | 0.13 | .04* | [0.01, 0.52] |
| Study quality | −0.01 | 0.09 | .89 | [−0.19, 0.17] | −0.02 | 0.09 | .84 | [−0.20, 0.17] |
| Effect size conversion | 0.09 | 0.14 | .51 | [−0.18, 0.36] | 0.05 | 0.14 | .73 | [−0.23, 0.33] |
| Sample characteristics | | | | | | | | |
| Female percentage | 0.23 | 0.55 | .67 | [−0.84, 1.30] | 0.68 | 0.61 | .26 | [−0.51, 1.87] |
| Crowdsourced versus other samples | 0.07 | 0.20 | .71 | [−0.31, 0.46] | 0.31 | 0.23 | .19 | [−0.15, 0.76] |
| Publication characteristics | | | | | | | | |
| Published versus not | 0.12 | 0.19 | .52 | [−0.25, 0.50] | 0.10 | 0.21 | .63 | [−0.32, 0.52] |
| Publication year | −0.01 | 0.02 | .42 | [−0.05, 0.02] | −0.03 | 0.02 | .10 | [−0.06, 0.01] |
| Country characteristics | | | | | | | | |
| Unemployment rate | | | | | −16.38 | 6.24 | .009** | [−28.62, −4.14] |
| GDP per capita (log) | | | | | −0.03 | 0.43 | .94 | [−0.88, 0.82] |
| College degree percentage | | | | | −0.66 | 1.30 | .61 | [−3.20, 1.88] |
| Internet use percentage | | | | | −1.51 | 2.88 | .60 | [−7.15, 4.12] |
| *N* | 8,383 | | | | 8,286 | | | |
| $k_{\text{sample}}$ | 37 | | | | 36 | | | |
| $k_{\text{es}}$ | 88 | | | | 85 | | | |

*Note.* *b* = coefficient in the metaregression analysis; *SE* = standard error; CI = confidence interval; AI = artificial intelligence; GDP = gross domestic product.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

**Table 5**
*Quadrants II, III, and IV Moderator Analyses: Metaregressions*

| Tested moderator | Model 1 *b* | *SE* | *p* | 95% CI | Model 2 *b* | *SE* | *p* | 95% CI |
|---|---|---|---|---|---|---|---|---|
| AI characteristics | | | | | | | | |
| Tangible robot versus intangible algorithm | 0.30 | 0.33 | .38 | [−0.36, 0.95] | 0.27 | 0.30 | .37 | [−0.32, 0.86] |
| Study characteristics | | | | | | | | |
| Behavioral versus attitudinal outcomes | 0.14 | 0.11 | .18 | [−0.07, 0.36] | 0.18 | 0.12 | .11 | [−0.04, 0.41] |
| Between-subjects versus within-subjects designs | −0.19 | 0.23 | .40 | [−0.64, 0.25] | 0.05 | 0.19 | .80 | [−0.32, 0.42] |
| Study quality | −0.12 | 0.11 | .29 | [−0.34, 0.10] | −0.06 | 0.10 | .57 | [−0.26, 0.14] |
| Effect size conversion | −0.35 | 0.06 | <.001*** | [−0.46, −0.24] | −0.35 | 0.05 | <.001*** | [−0.46, −0.24] |
| Sample characteristics | | | | | | | | |
| Female percentage | −0.28 | 0.60 | .64 | [−1.45, 0.90] | −0.75 | 0.54 | .16 | [−1.81, 0.31] |
| Crowdsourced versus other samples | −0.08 | 0.17 | .64 | [−0.42, 0.26] | 0.22 | 0.16 | .16 | [−0.09, 0.54] |
| Publication characteristics | | | | | | | | |
| Published versus not | 0.30 | 0.25 | .24 | [−0.20, 0.80] | 0.27 | 0.23 | .23 | [−0.17, 0.72] |
| Publication year | 0.03 | 0.02 | .12 | [−0.01, 0.08] | −0.004 | 0.02 | .82 | [−0.04, 0.03] |
| Country characteristics | | | | | | | | |
| Unemployment rate | | | | | 12.95 | 7.71 | .09 | [−2.16, 28.07] |
| GDP per capita (log) | | | | | 3.89 | 1.12 | <.001*** | [1.70, 6.08] |
| College degree percentage | | | | | −6.21 | 1.86 | <.001*** | [−9.85, −2.57] |
| Internet use percentage | | | | | −27.14 | 7.30 | <.001*** | [−41.44, −12.84] |
| *N* | 26,357 | | | | 21,882 | | | |
| $k_{\text{sample}}$ | 95 | | | | 80 | | | |
| $k_{\text{es}}$ | 277 | | | | 243 | | | |

*Note.* *b* = coefficient in the metaregression analysis; *SE* = standard error; CI = confidence interval; AI = artificial intelligence; GDP = gross domestic product.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

communication behavior (Aeschlimann et al., 2020), or attitudinal outcomes, such as trust (Höddinghaus et al., 2021; Yokoi et al., 2021), perceived fairness (Newman et al., 2020; Schlicker et al., 2021), and liking (Jago, 2019; Merritt et al., 2015).

As expected, when the outcome is behavioral (vs. attitudinal), AI appreciation is significantly weaker in Quadrant I (Table 4, Figure 5b). This result suggests that AI appreciation may be less pronounced in actual behaviors compared to attitudes. Meanwhile, outcome type (behavioral vs. attitudinal outcomes) is not a significant moderator in the other three quadrants (Table 5).

**Between-Subjects Versus Within-Subjects Designs.** Another moderator we tested was whether a study adopted a between-subjects design or a within-subjects design, because evaluation modes (e.g., joint vs. separate evaluation) may influence individuals' preferences in decision making (Bazerman et al., 1999; Hsee et al., 1999). An example of between-subjects designs was a study that manipulated whether a decision was attributed to a human or AI and then measured participants' evaluation of that decision (Newman et al., 2020). An example of within-subjects designs was a study that described a situation and asked participants to indicate their subjective perceptions of humans and AI separately (Byrd et al., 2021). Metaregressions found that when the study adopted a between-subjects (vs. within-subjects) design, AI appreciation was more pronounced in Quadrant I (Table 4, Figure 5c). Meanwhile, study design (between-subjects vs. within-subjects designs) is not a significant moderator in the other three quadrants (Table 5).

**Study Quality.** Testing study quality as a moderator is a common practice in meta-analyses (Rnic et al., 2023; Simonsohn et al., 2022; Spiegel et al., 2021). In our analyses, study quality is not a significant moderator in either Quadrant I (Table 4) or the other three quadrants (Table 5).

**Effect Size Conversion.** Effect size conversion may bias meta-analytic results (Poom & Af Wåhlberg, 2022), so we tested it as a potential moderator. Effect size conversion (1 = converted, 0 = not) is not a significant moderator in Quadrant I (Table 4). Meanwhile, it has a significant negative moderating effect in the other three quadrants (Table 5), suggesting that AI aversion is more pronounced in studies with converted effect sizes compared to those without (Figure 5e).

### *Sample Characteristics*

The percentage of females and whether a sample was crowdsourced are not significant moderators in either Quadrant I (Table 4) or the other three quadrants (Table 5).

### *Publication Characteristics*

Testing publication status and publication year as moderators is a common practice in meta-analyses (e.g., Liao et al., 2022). As shown in Tables 4 and 5, neither publication status nor publication year is a significant moderator in either Quadrant I (Table 4) or the other three quadrants (Table 5).

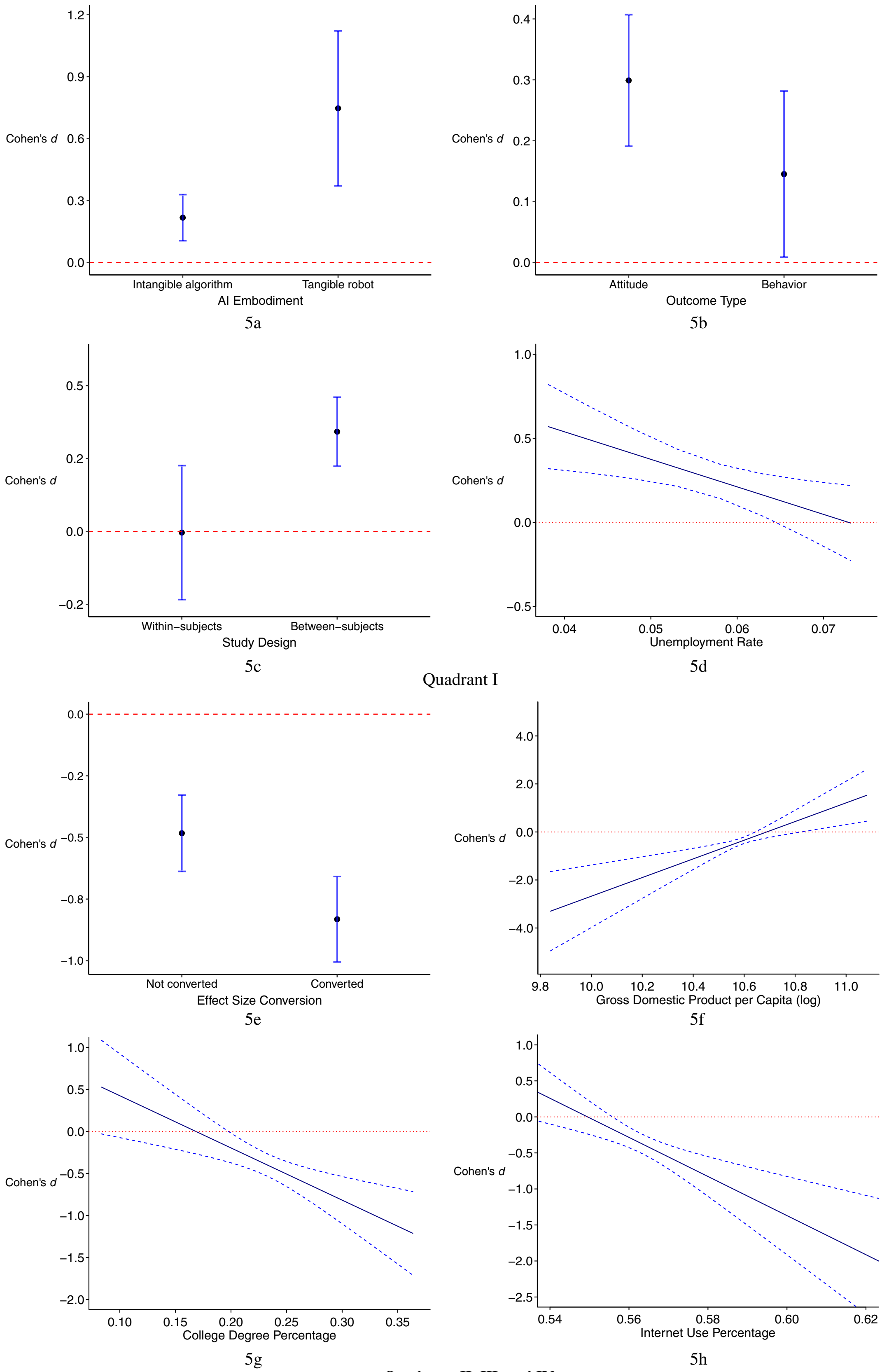
### *Country Characteristics*

We also explored the characteristics of the country in which each study was conducted. We added these country characteristics in Model 2 of Tables 4 and 5, as some studies either did not specify a country or included samples from multiple countries.[8]

[8] When a study did not specify the country of its sample but (a) all authors were in the same country and (b) the study did not use crowdsourced platforms, we used the country of the authors.

**Figure 5**

*Moderation Effects Plotted With the Moving Constant Technique*




*(figure continues)*

We tested unemployment rate, GDP per capita, college degree percentage, and internet use percentage as potential country-level moderators, as these factors may relate to AI use and preferences. For example, unemployment rate could be a moderator because people in high (vs. low) unemployment countries may be more concerned about AI replacing human labor (Yam et al., 2023). As expected, unemployment rate has a significant negative moderating effect in Quadrant I (Table 4), suggesting that AI appreciation is less pronounced in high unemployment countries (Figure 5d). Meanwhile, unemployment rate is not a significant moderator in the other three quadrants (Table 5).

GDP per capita is not a significant moderator in Quadrant I (Table 4). Meanwhile, it has a significant positive moderating effect in the other three quadrants (Table 5), suggesting that AI aversion is less pronounced in countries with high GDP per capita (Figure 5f).

College degree percentage is not a significant moderator in Quadrant I (Table 4). Meanwhile, it has a significant negative moderating effect in the other three quadrants (Table 5), suggesting that AI aversion is more pronounced in highly educated countries (Figure 5g).

Internet use percentage is not a significant moderator in Quadrant I (Table 4). Meanwhile, it has a significant negative moderating effect in the other three quadrants (Table 5), suggesting that AI aversion is more pronounced in countries with widespread internet usage (Figure 5h).

## Publication Bias

In meta-analyses, publication bias arises when statistically significant results are more likely to be published than nonsignificant ones. In alignment with the Capability–Personalization Framework, we separately analyzed publication bias for Quadrant I and publication bias for the other three quadrants combined.[9] To test potential publication bias, we conducted several tests in accordance with standard meta-analysis practices. Before presenting the results on publication bias, we note that the heterogeneity of effect sizes (as detailed above) makes the interpretation of these patterns difficult (Johnson, 2021).

### *Quadrant I*

First, the contour-enhanced funnel plot in Figure 6, left panel, depicts the relationship between effect size and standard error for Quadrant I. Regions of the plot are shaded to indicate different levels of statistical significance ($p$ < .10, .05, and .01). These “contours” help distinguish whether any asymmetry in the funnel plot is likely due to publication bias or other factors (Peters et al., 2008). We used Egger’s test (Egger et al., 1997) to formally test asymmetry in the funnel plots. The nonsignificant result from Egger’s test ($t$ = 1.73, $p$ = .08) indicates that the funnel plot is symmetric (i.e., no significant relationship between effect size and standard error).

Second, we conducted a regression analysis with publication status (1 = published, 0 = unpublished) as a covariate and effect size as the outcome. Publication status is not significantly associated with effect size ($b$ = 0.10, $SE$ = 0.12, $p$ = .43), suggesting no evidence of publication bias.

More importantly, to account for statistical dependencies, we conducted a precision-effect test (PET) and a precision-effect estimate with standard error (PEESE) metaregression using robust variance estimation with the R package *metafor* (Viechtbauer, 2010). “Because PET underestimates nonzero effects and PEESE overestimates null effects” (Agadullina & Lovakov, 2018, p. 712), a two-step conditional PET-PEESE procedure is recommended: If PET finds a significant effect, the PEESE estimate is preferred; if PET does not find a significant effect, the PET estimate is preferred (Agadullina & Lovakov, 2018; Stanley & Doucouliagos, 2014). The PET result ($b$ = 0.48, $SE$ = 0.55, $p$ = .38) is not significant, suggesting no evidence of publication bias.

### *Quadrants II, III, and IV*

First, the contour-enhanced funnel plot in Figure 6, right panel, depicts the relationship between effect size and standard error for Quadrants II, III, and IV. Egger’s test is significant ($t$ = 3.53, $p$ < .001), indicating that the funnel plot is asymmetric (i.e., a significant relationship between effect size and standard error). Visually, there appear to be some missing effect sizes in areas with large effect sizes. This indicates that selective nonreporting of nonsignificant results is not a major concern; rather, the funnel plot asymmetry might arise from factors other than publication bias (Peters et al., 2008).

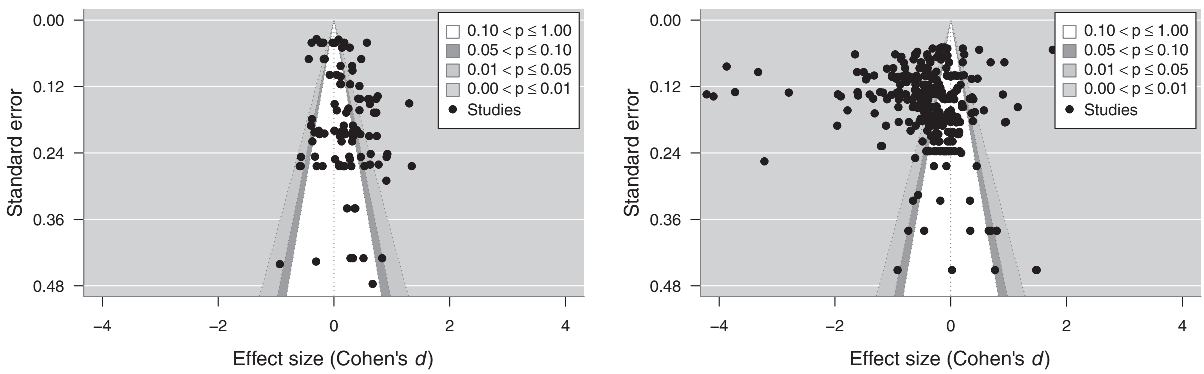
Second, we conducted a regression analysis with publication status (1 = published, 0 = unpublished) as a covariate and effect size as the outcome. Publication status is not significantly associated with effect size ($b$ = 0.11, $SE$ = 0.22, $p$ = .61), suggesting no evidence of publication bias.

More importantly, to account for statistical dependencies, we conducted a PET-PEESE metaregression with robust variance estimation (Viechtbauer, 2010). The PET result is not significant ($b$ = 1.74, $SE$ = 0.95, $p$ = .07), suggesting no evidence of publication bias.

[9] In Supplemental Materials, we analyzed publication bias separately for Quadrants II, III, and IV.

*Figure 5 Note*. (i) Positive $d$ values indicate that participants prefer AI over humans (i.e., AI appreciation), whereas negative $d$ values indicate that participants prefer humans over AI (i.e., AI aversion). (ii) Figure 5a (AI embodiment), 5b (outcome type), 5c (study design), and 5d (unemployment rate) show the significant moderation results of Quadrant I, while 5e (effect size conversion), 5f (gross domestic product per capita), 5g (college degree percentage), and 5h (internet use percentage) show the significant moderation results of Quadrants II, III, and IV. (iii) In Figure 5a, b, c, and e, the solid black points represent the mean Cohen’s $d$, and the error bars represent the 95% confidence intervals for the mean estimate. In Figure 5d, f, g, and h, solid regression lines represent the trends of Cohen’s $d$, while dotted lines represent 95% confidence intervals for these trends. AI = artificial intelligence. See the online article for the color version of this figure.

**Figure 6**
*Funnel Plots*




*Note*. Positive effect sizes indicate that participants prefer AI over humans (i.e., AI appreciation), whereas negative effect sizes indicate that participants prefer humans over AI (i.e., AI aversion). AI = artificial intelligence.



# Discussion

## Theoretical and Empirical Contributions

The present research offers important theoretical and empirical contributions. To begin with, we address the debate of whether people are averse to or appreciative of AI: While some studies in the literature find that people prefer humans over AI (AI aversion), others find the opposite (AI appreciation). As discussed in the Introduction, researchers across various disciplines—including economics, philosophy, and information science—have sought to explain AI aversion or AI appreciation (Frey & Osborne, 2017; Hou & Jung, 2021; Korinek & Stiglitz, 2019; Müller, 2020). The few reviews and meta-analyses directly examining individuals' attitudes toward AI have focused on specific domains, such as health care (A. T. Young et al., 2021) and education (Chiu et al., 2023), without offering a cross-domain theoretical framework, not to mention reconciling the conflicting findings on AI aversion versus AI appreciation. To address these knowledge gaps, we propose the Capability–Personalization Framework of AI aversion versus AI appreciation. Our framework identifies two key dimensions that influence individuals' decisions to rely on AI versus humans: (a) perceived capability of AI and (b) perceived necessity for personalization in a decision context. Our integrative framework moves beyond the binary question of whether people prefer AI over humans to highlight the importance of understanding when people prefer AI over humans.

Taking a step further, we tested our Capability–Personalization Framework in a meta-analysis of 442 effect sizes from 163 studies ($N = 82{,}078$). Our meta-analysis shows that AI appreciation occurs when AI is perceived as more capable than humans and personalization is perceived as unnecessary in a given decision context; otherwise, AI aversion occurs. In other words, while perceived AI capability is necessary for AI appreciation, it is not sufficient, as the perceived necessity of personalization also plays a crucial role in a given decision context. These insights contribute to the broader literature on preference for AI versus humans.

Moreover, our meta-analysis provides additional insights by examining a broad set of potential moderators: AI characteristics, study characteristics, sample characteristics, publication characteristics, and country characteristics. First, we found that attitudinal outcomes have larger effect sizes (in magnitude) than behavioral outcomes for AI appreciation, suggesting that AI appreciation may weaken when it comes to actual behaviors. This result is consistent with the notion that behaviors may be more resistant to influence than attitudes (Bezrukova et al., 2016; Glasman & Albarracín, 2006; Roesler et al., 2021). Relatedly, this result suggests that people's attitudinal appreciation of AI may not always translate into behavioral adoption of AI. For example, ethical concerns such as data breaches and misuse may discourage individuals from using AI, even if they appreciate it attitudinally (Kodapanakkal et al., 2020; Querci et al., 2022).

Second, we found that when AI is a tangible robot (vs. intangible algorithm), AI appreciation is more pronounced. This finding suggests that one way to increase AI appreciation is through physical embodiment. Compared to intangible algorithms, tangible robots can engage in a wider range of social interactions with humans (e.g., eye contact, touch), which could foster greater AI appreciation (Glikson & Woolley, 2020; Willemse & Van Erp, 2019). Our finding highlights the need for interdisciplinary research that integrates insights from psychology, computer science, engineering, and design to deepen our understanding of how AI embodiment shapes preference for AI.

Third, we found that AI appreciation is less pronounced in countries with high (vs. low) unemployment rates, a finding that remains robust when controlling for potential confounds. This finding suggests that perceived employment threat from AI may diminish appreciation for the technology. To enhance AI appreciation, it may be essential to address concerns regarding AI's impact on job opportunities. In addition, our finding hints at the possibility that AI could exacerbate economic inequality between countries with varying unemployment rates: If people in countries with higher unemployment rates are less appreciative of AI and, consequently, more reluctant to adopt it, these countries may fall further behind in technological advancement. These insights expand the emerging literature on AI-related threats (Yam et al., 2023).

## Practical Implications

Understanding public reactions to AI has profound implications for AI developers, organizations, and individual users. First, AI developers and organizations should consider not only AI's capability but also its usage context. Our Capability–Personalization Framework suggests that AI appreciation occurs only when AI is perceived as more capable than humans and personalization is perceived as unnecessary in a given decision context. For example, *AlphaGo* and other chess-related AI are appreciated by the public likely because they both feature high capability and are contextually characterized by low personalization. To boost AI adoption, developers and organizations could prioritize contexts characterized by low personalization or work to reduce users' perceived necessity for personalization.

Second, individual users should cultivate a balanced view of AI. Our framework and meta-analysis suggest that AI aversion occurs if personalization is perceived as necessary in a given decision context—even when AI is objectively more capable than humans. For example, even if a medical AI makes accurate recommendations based on extensive patient data, some patients may still instinctively lean toward AI aversion. Individuals should be aware of such biases and critically assess whether personalization is genuinely necessary in their specific context.

## Limitations and Future Directions

The current research has several limitations, which provide opportunities for future research. First, while our Capability–Personalization Framework concisely encapsulates the large number of studies in the meta-analysis, we acknowledge that our two-dimensional framework is not exhaustive. Factors beyond perceived AI capability and perceived necessity for personalization may also influence preference for AI. For example, Bigman et al. (2023) tested the algorithmic outrage deficit hypothesis in the context of HR practices and found that people expressed less moral outrage toward AI's (vs. humans') gender discrimination because they perceive AI as having less intention to discriminate.

Second, although the two dimensions (perceived AI capability and perceived necessity for personalization) were coded by a large number of independent coders with higher intercoder reliability, the use of a single item to measure each dimension is a methodological limitation. Specifically, this method limited our ability to conduct a factor analysis to validate the two dimensions. To mitigate this limitation and ascertain the usefulness of our framework, we coded two additional, theoretically related decision context characteristics: "analytical" and "emotional." Analytical contexts are contexts "relating to or using analysis or logical reasoning" (New Oxford American Dictionary, n.d.), while emotional contexts are contexts involving human emotions. As detailed in Supplemental Tables S9–S14, we found that the two dimensions of the Capability–Personalization Framework can better explain AI aversion versus AI appreciation than the "analytical" and "emotional" dimensions. These results thus provide further support for our Capability–Personalization Framework.

Third, for each study in the meta-analysis, the capability of AI (vs. humans) was rated in 2022; these ratings may differ from participants' perceptions of AI capability when the study was conducted. Nevertheless, our meta-analysis tested the moderating effect of publication year, which accounts for perceived AI capability at the time when a study was published. Analyses found that publication year is not a significant moderator—for either Quadrant I (high AI capability and low personalization; Table 4) or the other three quadrants (Table 5). We encourage future studies to assess perceived AI capability in real time to ascertain whether real-time ratings of perceived AI capability would yield consistent results, thereby further validating our Capability–Personalization Framework. Moreover, all studies in our meta-analysis were conducted before the launch of ChatGPT in November 2022. Given the revolutionary nature of ChatGPT and other generative AI models, people's perceptions of AI capability may have evolved over time. Thus, future studies could test our framework in the post-ChatGPT era.

Fourth, some categorical moderators (e.g., AI characteristics, publication status) are unevenly distributed across values, with certain values being represented by relatively few studies. For such cases, it is important to interpret the moderation results with caution (Huedo-Medina et al., 2006). For example, although publication status was not found to be a significant moderator in our meta-analysis, we interpret this null result cautiously because only 11.5% of the studies in the meta-analysis were unpublished. Also, since the omission of unpublished studies may bias effect size estimates (Rosenthal & DiMatteo, 2001), future meta-analyses should include more unpublished studies if available.

Fifth, while it is customary to consider country-level moderators in meta-analyses (e.g., Cheng et al., 2013; French et al., 2018), the samples included in the meta-analysis might not be nationally representative. Moreover, most samples (study level: 88.7%; effect-size level: 92.2%) in the meta-analysis belong to western, educated, industrialized, rich, and democratic (WEIRD) countries (Henrich et al., 2010). Although our additional moderator analyses indicate that the WEIRD variable is not a significant moderator in either Quadrant I or the other three quadrants, these nonsignificant results may be driven by the underrepresentation of non-WEIRD samples in the studies. As culture is a meaning-making framework that shapes everyday life (Lu, Benet-Martínez, & Wang, 2023; Lu, Song, & Zhang, in press; Oyserman, 2011, 2017), psychological patterns in WEIRD countries may be different from those in non-WEIRD countries (Brady et al., 2018; Henrich et al., 2010). Additionally, while some of the samples (study level: 13.7%; effect-size level: 10.5%) originate from non-English speaking countries (e.g., China, Germany, Japan, and Switzerland), our literature search was confined to articles written in English. This mono-language bias may limit the generalizability of our findings. Thus, we encourage future research to use more nationally representative samples and to include a broader range of countries (especially non-WEIRD and non-English speaking countries) to test the robustness of country-level moderator results.

Sixth, while our meta-analysis considered a broad set of potential moderators (i.e., AI characteristics, study characteristics, sample characteristics, publication characteristics, and country characteristics), other moderators may also be at play. Following anonymous reviewers' suggestions, we attempted to code additional moderators, including whether AI employs supervised learning/unsupervised learning/deep learning/reinforcement learning, AI adaptability, AI reliability, AI transparency, whether AI has privacy or security features, whether AI is specialized or general, and decision contexts (business, health care, social, and others). However, we were unable to test most of these variables as moderators due to either a lack of codable information in the studies or minimal variance in the variables across the studies. The few testable exploratory variables (e.g., AI reliability, AI transparency, and decision contexts) did not emerge as significant moderators in either Quadrant I or the other three quadrants. As more empirical studies on AI aversion and AI appreciation are conducted, future meta-analyses could examine potential moderators more systematically.

Seventh, while some studies included in this meta-analysis were experimental, we emphasize that meta-analysis is primarily a correlational method, particularly concerning the moderator analyses. Hence, the results reported in our meta-analysis do not indicate causal relations.

Eighth, although we followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines closely to ensure transparency and reproducibility, the meta-analysis was not preregistered, and some analytical decisions were informed by multiple rounds of reviewer feedback. We thus recommend future research to replicate our meta-analysis.

## Conclusions

Overall, our Capability–Personalization Framework elucidates the conditions under which people are averse to or appreciative of AI, thereby reconciling the conflicting findings in the literature on AI aversion versus AI appreciation. Consistent with this framework, our meta-analysis of 442 effect sizes from 163 studies shows that AI appreciation occurs when (a) AI is perceived as more capable than humans and (b) personalization is perceived as unnecessary in a given decision context; otherwise, AI aversion occurs. Our integrative framework and meta-analysis provide valuable insights for AI developers and users as AI continues to transform human life.

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