SUPPLEMENTAL MATERIALS

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

Table S1
Moderators Tested in the Meta-Analysis

Moderator	Definition	Data source
AI characteristics		
Tangible robot vs. intangible algorithm	Whether the AI is a tangible robot or an intangible algorithm; 1 = tangible robots, 0 = intangible algorithms	article
Study characteristics		
Behavioral vs. attitudinal outcomes	Whether the outcome variable is a behavior or an attitude; 1 = behavioral outcomes, 0 = attitudinal outcomes	article
Between-subjects vs. within-subjects designs	Whether the study used a between-subjects or within-subjects design; 1 = between-subjects design, 0 = within-subjects design	article
Study quality	Four indicators: (a) whether a study conducted power analysis (1 = yes, 0 = no/unknown), (b) whether a study reported preregistration (1 = yes, 0 = no/unknown), (c) whether a study reported excluding participants from analyses (1 = yes, 0 = no/unknown), and (d) whether a study had an attention check (1 = yes, 0 = no/unknown). We calculated study quality by averaging the standardized scores of the four indicators.	article
Effect size conversion	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. 1 = converted, 0 = not	article
Sample characteristics		
Female percentage	The proportion of the sample that is female	article
Crowdsourced vs. other samples	1 = crowdsourced sample, 0 = other sample	article
Publication characteristics		
Publication vs. not	1 = published, 0 = unpublished	article

Publication year	Publication year of the article	article
Country characteristics		
Unemployment rate	The proportion of the country's labor force that is unemployed but available and looking for a job	https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS
GDP per capita	The country's gross domestic product divided by the midyear population	https://data.worldbank.org/indicator/NY.GDP.PCAP.CD
College degree percentage	The country's percentage of the population that is age 25+ with tertiary schooling	https://databank.worldbank.org/source/education-statistics-%5e-all-indicators
Internet use percentage	The country's percentage of the population that use the internet	https://data.worldbank.org/indicator/IT.NET.USER.ZS

Table S2

Articles Included in the Meta-Analysis

Authors	Year	Title	Source
Acikgoz et al.	2020	Justice perceptions of artificial intelligence in selection	International Journal of Selection and Assessment
Aeschlimann et al.	2020	Communicative and social consequences of interactions with voice assistants	Computers in Human Behavior
Babel et al.	2021	Small talk with a robot? The impact of dialog content, talk initiative, and gaze behavior of a social robot on trust, acceptance, and proximity	International Journal of Social Robotics
Bai et al.	2022	The impacts of algorithmic work assignment on fairness perceptions and productivity: Evidence from field experiments	Manufacturing & Service Operations Management
Banks	2021	Good robots, bad robots: Morally valenced behavior effects on perceived mind, morality, and trust	International Journal of Social Robotics
Ben-David & Sade	2019	Robo-advisor adoption, willingness to pay, and trust—an experimental investigation	SSRN
Bigman & Gray	2018	People are averse to machines making moral decisions	Cognition
Byrd et al.	2021	Robot vs human: Expectations performances and gaps in off-premise restaurant service modes	International Journal of Contemporary Hospitality Management
Cadario et al.	2021	Understanding, explaining, and utilizing medical artificial intelligence	Nature Human Behaviour
Castelo et al.	2019	Task-dependent algorithm aversion	Journal of Marketing Research
Chan & Tung	2019	Examining the effects of robotic service on brand experience: The moderating role of hotel segment	Journal of Travel & Tourism Marketing
Daschner & Obermaier	2022	Algorithm aversion? On the influence of advice accuracy on trust in algorithmic advice	Journal of Decision Systems
Dietvorst et al.	2015	Algorithm aversion: People erroneously avoid algorithms after seeing them err	Journal of Experimental Psychology: General
Dineen et al.	2004	Perceived fairness of web-based applicant screening procedures: Weighing the rules of justice and the role of individual differences	Human Resource Management
Dzindolet et al.	2002	The perceived utility of human and automated aids in a visual detection task	Human Factors
Dzindolet et al.	2003	The role of trust in automation reliance	International Journal of Human-Computer Studies
Edwards et al.	2014	Is that a bot running the social media feed? Testing the differences in perceptions of communication quality for a human agent and a bot agent on Twitter	Computers in Human Behavior
Efendić et al.	2020	Slow response times undermine trust in algorithmic (but not human) predictions	Organizational Behavior and Human Decision Processes
Goodyear et al.	2017	An fMRI and effective connectivity study investigating miss errors during advice utilization from human and machine agents	Social Neuroscience
Goodyear et al.	2016	Advice taking from humans and machines: An fMRI and effective connectivity study	Frontiers in Human Neuroscience
Graefe et al.	2018	Readers' perception of computer-generated news: Credibility, expertise, and readability	Journalism

Granulo et al.	2021	Preference for human (vs. robotic) labor is stronger in symbolic consumption contexts	Journal of Consumer Psychology
Hobson et al.	2021	Artificial fairness? Trust in algorithmic police decision-making	Journal of Experimental Criminology
Höddinghaus et al.	2021	The automation of leadership functions: Would people trust decision algorithms?	Computers in Human Behavior
Hou & Jung	2021	Who is the expert? Reconciling algorithm aversion and algorithm appreciation in AI-supported decision making	Proceedings of the ACM on Human-Computer Interaction
Howard et al.	2020	Implementation of an automated scheduling tool improves schedule quality and resident satisfaction	PLoS ONE
Ingrams et al.	2022	In AI we trust? Citizen perceptions of AI in government decision making	Policy & Internet
Jago	2019	Algorithms and authenticity	Academy of Management Discoveries
Jakesch et al.	2019	AI-mediated communication: How the perception that profile text was written by AI affects trustworthiness	Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems
Juravle et al.	2020	Trust in artificial intelligence for medical diagnoses	Progress in Brain Research
Kaibel et al.	2019	Applicant perceptions of hiring algorithms-uniqueness and discrimination experiences as moderators	Academy of Management Proceedings
Kaufmann & Budescu	2020	Do teachers consider advice? On the acceptance of computerized expert models	Journal of Educational Measurement
Kohn et al.	2018	Trust repair strategies with self-driving vehicles: An exploratory study	Proceedings of the Human Factors and Ergonomics Society Annual Meeting
Laakasuo et al.	2021	Moral uncanny valley: A robot's appearance moderates how its decisions are judged	International Journal of Social Robotics
Langer et al.	2020	Highly automated interviews: Applicant reactions and the organizational context	Journal of Managerial Psychology
Langer et al.	2019	Highly automated job interviews: Acceptance under the influence of stakes	International Journal of Selection and Assessment
Langer et al.	2022	Trust in artificial intelligence: Comparing trust processes between human and automated trustees in light of unfair bias	Journal of Business and Psychology
Langer et al.	2017	Examining digital interviews for personnel selection: Applicant reactions and interviewer ratings	International Journal of Selection and Assessment
Lee	2018	Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management	Big Data & Society
Lennartz et al.	2021	Use and control of artificial intelligence in patients across the medical workflow: Single-center questionnaire study of patient perspectives	Journal of Medical Internet Research
Lewandowsky et al.	2000	The dynamics of trust: Comparing humans to automation	Journal of Experimental Psychology: Applied

Li et al.	2020	Who should provide clothing recommendation services: Artificial intelligence or human experts?	Journal of Information Technology Research
Logg et al.	2019	Algorithm appreciation: People prefer algorithmic to human judgment	Organizational Behavior and Human Decision Processes
Longoni & Cian	2022	Artificial intelligence in utilitarian vs. hedonic contexts: The “word-of-machine” effect	Journal of Marketing
Longoni et al.	2019	Resistance to medical artificial intelligence	Journal of Consumer Research
Lyons & Stokes	2012	Human–human reliance in the context of automation	Human Factors
Madhavan & Wiegmann	2007	Effects of information source, pedigree, and reliability on operator interaction with decision support systems	Human Factors
Marcinkowski et al.	2020	Implications of AI (un-)fairness in higher education admissions: The effects of perceived AI (un-)fairness on exit, voice and organizational reputation	Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency
Merkle	2019	Customer responses to service robots: Comparing human-robot interaction with human-human interaction	Proceedings of the 52nd Hawaii International Conference on System Sciences
Merritt et al.	2015	Attitudinal predictors of relative reliance on human vs. automated advisors	International Journal of Human Factors and Ergonomics
Mühl et al.	2020	Get ready for being chauffeured: Passenger’s preferences and trust while being driven by human and automation	Human Factors
Nagtegaal	2021	The impact of using algorithms for managerial decisions on public employees’ procedural justice	Government Information Quarterly
Newman et al.	2020	When eliminating bias isn’t fair: Algorithmic reductionism and procedural justice in human resource decisions	Organizational Behavior and Human Decision Processes
Niszczota & Kaszás	2020	Robo-investment aversion	PLoS ONE
Noble et al.	2021	The procedural and interpersonal justice of automated application and resume screening	International Journal of Selection and Assessment
Nozawa et al.	2022	Consumer responses to the use of artificial intelligence in luxury and non-luxury restaurants	Food Quality and Preference
Ötting & Maier	2018	The importance of procedural justice in human–machine interactions: Intelligent systems as new decision agents in organizations	Computers in Human Behavior
Palmeira & Spassova	2015	Consumer reactions to professionals who use decision aids	European Journal of Marketing
Pearson et al.	2016	Differences in trust between human and automated decision aids	Proceedings of the Symposium and Bootcamp on the Science of Security
Prahl & Van Swol	2021	Out with the humans, in with the machines?: Investigating the behavioral and psychological effects of replacing human advisors with a machine	Human-Machine Communication
Prahl & Van Swol	2017	Understanding algorithm aversion: When is advice from automation discounted?	Journal of Forecasting

Promberger & Baron	2006	Do patients trust computers?	Journal of Behavioral Decision Making
Renier et al.	2021	To err is human, not algorithmic – Robust reactions to erring algorithms	Computers in Human Behavior
Sanders et al.	2017	Trust and prior experience in human-robot interaction	Proceedings of the Human Factors and Ergonomics Society Annual Meeting
Schlicker et al.	2021	What to expect from opening up 'black boxes'? Comparing perceptions of justice between human and automated agents	Computers in Human Behavior
Shank	2013	Are computers good or bad for business? How mediated customer–computer interaction alters emotions, impressions, and patronage toward organizations	Computers in Human Behavior
Sharan & Romano	2020	The effects of personality and locus of control on trust in humans versus artificial intelligence	Heliyon
Sinha & Swearingen	2001	Comparing recommendations made by online systems and friends	DELOS Workshops/Conferences
Suen et al.	2019	Does the use of synchrony and artificial intelligence in video interviews affect interview ratings and applicant attitudes?	Computers in Human Behavior
Sundar & Nass	2000	Source orientation in human-computer interaction: Programmer, networker, or independent social actor	Communication Research
Thuillard et al.	2022	When humans and computers induce social stress through negative feedback: Effects on performance and subjective state	Computers in Human Behavior
van der Kaa & Krahmer	2014	Journalist versus news consumer: The perceived credibility of machine written news	Proceedings of the Computation+Journalism conference
Vodrahalli et al.	2022	Do humans trust advice more if it comes from AI?: An analysis of human-AI interactions	arXiv
Wölker & Powell	2021	Algorithms in the newsroom? News readers' perceived credibility and selection of automated journalism	Journalism
Waddell	2018	A robot wrote this? How perceived machine authorship affects news credibility	Digital Journalism
Waddell	2019	Can an algorithm reduce the perceived bias of news? Testing the effect of machine attribution on news readers' evaluations of bias, anthropomorphism, and credibility	Journalism & Mass Communication Quarterly
Wang et al.	2020	When expert recommendation contradicts peer opinion: Relative social influence of valence, group identity and artificial intelligence	Computers in Human Behavior
Yeomans et al.	2019	Making sense of recommendations	Journal of Behavioral Decision Making
Yokoi & Nakayachi	2021	Trust in autonomous cars: Exploring the role of shared moral values, reasoning, and emotion in safety-critical decisions	Human Factors
Yokoi et al.	2021	Artificial intelligence is trusted less than a doctor in medical treatment decisions: Influence of perceived care and value similarity	International Journal of Human–Computer Interaction
Young & Monroe	2019	Autonomous morals: Inferences of mind predict acceptance of AI behavior in sacrificial moral dilemmas	Journal of Experimental Social Psychology

Yun et al.	2021	Behavioral and neural evidence on consumer responses to human doctors and medical artificial intelligence	Psychology & Marketing
Zhang et al.	2021	Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services	Journal of Services Marketing

Meta-Analysis Using the Median Values (of AI Capability and Personalization) as Cutoff Points
Tables S3-S4

Table S3

Meta-Regression of Preference for AI (vs. Humans) (Using the Median Values as Cutoff Points)

Variables	*b*	*SE*	*t*	*p*
Intercept = Quadrant I (high AI capability and low personalization) [reference group]	0.20	0.09	2.32	.02
Quadrant II (high AI capability and high personalization)	-0.57	0.15	-3.70	< .001
Quadrant III (low AI capability and high personalization)	-0.60	0.13	-4.61	< .001
Quadrant IV (low AI capability and low personalization)	-0.90	0.13	-6.85	< .001

Note. *b* = coefficient in the meta-regression, *SE* = standard error. 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.

Table S4

Meta-Analysis of Preference for AI (vs. Humans) in Each of the Four Quadrants (Using the Median Values as Cutoff Points)

Condition	k_{sample}	k_{es}	N	d	SD	95% CI	80% prediction interval	I^2
Quadrant I (high AI capability and low personalization)	52	122	9,693	0.20	0.35	[0.09, 0.30]	[-0.26, 0.66]	92.14%
Quadrant II (high AI capability and high personalization)	23	56	4,902	-0.36	0.40	[-0.53, -0.20]	[-0.88, 0.15]	91.96%
Quadrant III (low AI capability and high personalization)	38	144	11,218	-0.40	0.58	[-0.59, -0.22]	[-1.15, 0.35]	96.50%
Quadrant IV (low AI capability and low personalization)	37	92	12,029	-0.70	0.90	[-0.99, -0.41]	[-1.87, 0.46]	98.35%

Note. 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. 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).

Meta-Analysis after Removing the 8 Outliers
Tables S5-S6

Table S5

Meta-Regression of Preference for AI (vs. Humans) (After Removing the 8 Outliers)

Variables	*b*	*SE*	*t*	*p*
Intercept = Quadrant I (high AI capability and low personalization) [reference group]	0.27	0.06	4.36	< .001
Quadrant II (high AI capability and high personalization)	-0.71	0.13	-5.68	< .001
Quadrant III (low AI capability and high personalization)	-0.63	0.08	-7.63	< .001
Quadrant IV (low AI capability and low personalization)	-0.74	0.09	-8.05	< .001

Note. *b* = coefficient in the meta-regression, *SE* = standard error. 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.

Table S6

Meta-Regression of Preference for AI (vs. Humans) in Each of the Four Quadrants (After Removing the 8 Outliers)

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	181	15,853	-0.36	0.40	[-0.47, -0.25]	[-0.87, 0.15]	92.77%
Quadrant IV (low AI capability and low personalization)	35	92	9,615	-0.47	0.49	[-0.64, -0.31]	[-1.12, 0.17]	94.15%

Note. 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, and CI = confidence interval, I^2 = percentage of the total variability due to heterogeneity. 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).

Meta-Analysis after Excluding Studies that Scored Below the Median Value of Study Quality
Tables S7-S8

Table S7

Meta-Regression of Preference for AI (vs. Humans) (After Excluding Studies that Scored Below the Median Value of Study Quality)

Variables	*b*	*SE*	*t*	*p*
Intercept = Quadrant I (high AI capability and low personalization) [reference group]	0.25	0.12	2.07	.04
Quadrant II (high AI capability and high personalization)	-0.65	0.19	-3.37	< .001
Quadrant III (low AI capability and high personalization)	-0.69	0.15	-4.63	< .001
Quadrant IV (low AI capability and low personalization)	-0.93	0.16	-5.76	< .001

Note. *b* = coefficient in the meta-regression, *SE* = standard error. 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.

Table S8

Meta-Regression of Preference for AI (vs. Humans) in Each of the Four Quadrants (After Excluding Studies that Scored Below the Median Value of Study Quality)

Condition	k_{sample}	k_{es}	N	d	SD	95% CI	80% prediction interval	I^2
Quadrant I (high AI capability and low personalization)	19	33	5,900	0.23	0.26	[0.11, 0.36]	[-0.11, 0.57]	90.50%
Quadrant II (high AI capability and high personalization)	12	24	3,343	-0.39	0.09	[-0.46, -0.31]	[-0.52, -0.26]	36.34%
Quadrant III (low AI capability and high personalization)	36	139	13,211	-0.44	0.57	[-0.62, -0.25]	[-1.18, 0.30]	96.85%
Quadrant IV (low AI capability and low personalization)	24	54	7,821	-0.67	0.66	[-0.94, -0.41]	[-1.54, 0.19]	97.29%

Note. 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, and CI = confidence interval, I^2 = percentage of the total variability due to heterogeneity. 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).

Meta-Analysis Using "Analytical" and/or "Emotional" Dimensions
Tables S9-S14

We conducted additional analyses using the analytical and emotional characteristics of tasks. Analytical contexts are contexts "relating to or using analysis or logical reasoning" (New Oxford American Dictionary, n.d.), while emotional contexts are contexts in which human emotions are involved. We asked 13 coders to code how analytical and emotional the decision contexts are. To assess the "analytical" dimension, we asked the coders to rate the extent to which the decision contexts involve logical reasoning (1 = "not at all," 6 = "very much"). To assess the "emotional" dimension, we asked the coders to rate the extent to which the decision contexts involve emotions (1 = "not at all," 6 = "very much"). Using these two items, 13 coders independently rated the 93 decision contexts (randomly ordered). The average interrater agreement (James et al., 1984) was high for both the analytical (mean r_{wg} = .83, median r_{wg} = .84) and emotional dimensions (mean r_{wg} = .86, median r_{wg} = .88). Therefore, we averaged the coder ratings for each decision context to calculate the (a) analytical and (b) emotional dimensions. We conducted supplementary meta-analyses via three approaches. First, we conducted similar analyses to the main analyses but using the analytical dimension together with the personalization dimension (rather than the AI capability with the personalization dimensions). Second, we conducted additional analyses by testing the AI capability dimension together with the emotional dimension. Third, we conducted additional analyses by testing the analytical dimension together with the emotional dimension. Results showed that none of the three combinations can significantly predict AI appreciation (Tables S11-S16).

Table S9

Meta-Regression of Preference for AI (vs. Humans) (Analytical + Personalization Dimensions)

Variables	*b*	*SE*	*t*	*p*
Intercept = Quadrant I (high analytical and low personalization) [reference group]	-0.20	0.08	-2.45	.014
Quadrant II (high analytical and high personalization)	-0.18	0.12	-1.49	.14
Quadrant III (low analytical and high personalization)	-0.28	0.27	-1.02	.31
Quadrant IV (low analytical and low personalization)	0.29	0.22	1.32	.19

Note. *b* = coefficient in the meta-regression, *SE* = standard error. 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.

Table S10

Meta-Analysis of Preference for AI (vs. Humans) in Each of the Four Quadrants (Analytical + Personalization Dimensions)

Condition	k_{sample}	k_{es}	N	d	SD	95% CI	80% prediction interval	I^2
Quadrant I (high analytical and low personalization)	71	162	15,792	-0.20	0.84	[-0.40, -0.004]	[-1.29, 0.88]	97.96%
Quadrant II (high analytical and high personalization)	60	201	17,519	-0.39	0.48	[-0.51, -0.26]	[-1.01, 0.24]	94.88%
Quadrant III (low analytical and high personalization)	7	10	1,734	-0.49	0.58	[-0.92, -0.05]	[-1.27, 0.30]	97.39%
Quadrant IV (low analytical and low personalization)	12	41	2,797	0.08	0.56	[-0.25, 0.41]	[-0.67, 0.83]	97.92%

Note. 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. 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).

Table S11

Meta-Regression of Preference for AI (vs. Humans) (AI Capability + Emotional Dimensions)

Variables	*b*	*SE*	*t*	*p*
Intercept = Quadrant I (high AI capability and low emotional) [reference group]	0.06	0.10	0.59	.55
Quadrant II (high AI capability and high emotional)	0.12	0.18	0.68	.50
Quadrant III (low AI capability and high emotional)	-0.56	0.13	-4.26	< .001
Quadrant IV (low AI capability and low emotional)	-0.58	0.15	-3.76	< .001

Note. *b* = coefficient in the meta-regression, *SE* = standard error. 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.

Table S12

Meta-Analysis of Preference for AI (vs. Humans) in Each of the Four Quadrants (AI Capability + Emotional Dimensions)

Condition	k_{sample}	k_{es}	N	d	SD	95% CI	80% prediction interval	I^2
Quadrant I (high AI capability and low emotional)	40	83	9,233	0.07	0.35	[-0.05, 0.18]	[-0.39, 0.52]	90.58%
Quadrant II (high AI capability and high emotional)	20	50	2,951	0.18	0.56	[-0.08, 0.43]	[-0.56, 0.91]	97.24%
Quadrant III (low AI capability and high emotional)	60	194	17,619	-0.50	0.62	[-0.66, -0.34]	[-1.30, 0.30]	96.49%
Quadrant IV (low AI capability and low emotional)	30	87	8,039	-0.53	0.90	[-0.85, -0.20]	[-1.71, 0.65]	98.68%

Note. 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. 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).

Table S13

Meta-Regression of Preference for AI (vs. Humans) (Analytical + Emotional Dimensions)

Variables	*b*	*SE*	*t*	*p*
Intercept = Quadrant I (high analytical and low emotional) [reference group]	-0.17	0.09	-1.92	.055
Quadrant II (high analytical and high emotional)	-0.24	0.12	-1.96	.0499
Quadrant III (low analytical and high emotional)	0.20	0.21	0.94	.34
Quadrant IV (low analytical and low emotional)	-0.32	0.30	-1.07	.28

Note. *b* = coefficient in the meta-regression, *SE* = standard error. 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.

Table S14

Meta-Analysis of Preference for AI (vs. Humans) in Each of the Four Quadrants (Analytical + Emotional Dimensions)

Condition	k_{sample}	k_{es}	N	d	SD	95% CI	80% prediction interval	I^2
Quadrant I (high analytical and low emotional)	64	160	16,342	-0.17	0.73	[-0.35, 0.02]	[-1.11, 0.78]	97.86%
Quadrant II (high analytical and high emotional)	67	203	16,969	-0.40	0.65	[-0.56, -0.24]	[-1.24, 0.44]	96.49%
Quadrant III (low analytical and high emotional)	13	41	3,601	0.03	0.67	[-0.34, 0.40]	[-0.86, 0.92]	98.56%
Quadrant IV (low analytical and low emotional)	6	10	930	-0.51	0.36	[-0.83, -0.20]	[-1.02, -0.003]	92.41%

Note. 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. 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).

We conducted analyses by quadrant instead of testing the interactive effect of perceived AI capability and personalization because, according to the Capability–Personalization Framework, individuals appreciate AI only when AI is perceived as more capable than humans and personalization is unnecessary in a given decision context (i.e., Quadrant I); otherwise (i.e., the other three quadrants), AI aversion occurs. Dividing the studies into four quadrants thus directly tests the framework. Importantly, whether the framework is supported is not equivalent to whether the interactive effect of perceived AI capability and personalization is significant. For instance, suppose that the Cohen's *d*s of Quadrants I, II, III, and IV were 0.2 (AI appreciation), -0.2 (AI aversion), -0.6 (AI aversion), and -0.2 (AI aversion), respectively; in this case, the framework would be supported (i.e., AI appreciation occurs only in Quadrant I), but the interactive effect of the two dimensions would be zero because the distance between Quadrants I and IV is the same as the distance between Quadrants II and III (as illustrated by Figure S1a). On the other hand, suppose that the Cohen's *d*s of Quadrants I, II, III, and IV were -0.2, -0.2, -0.6, and -0.2 (i.e., AI aversion in all four quadrants), respectively; in this case, the framework would not be supported—even though there would be an interactive effect of the two dimensions because the distance between Quadrants I and IV is not equal to the distance between Quadrants II and III (as illustrated by Figure S1b).

Figure S1

Hypothetical Scenarios Illustrating That Whether the Capability–Personalization Framework Is Supported Is Not Equivalent to Whether the Interactive Effect of Perceived AI Capability and Personalization Is Significant

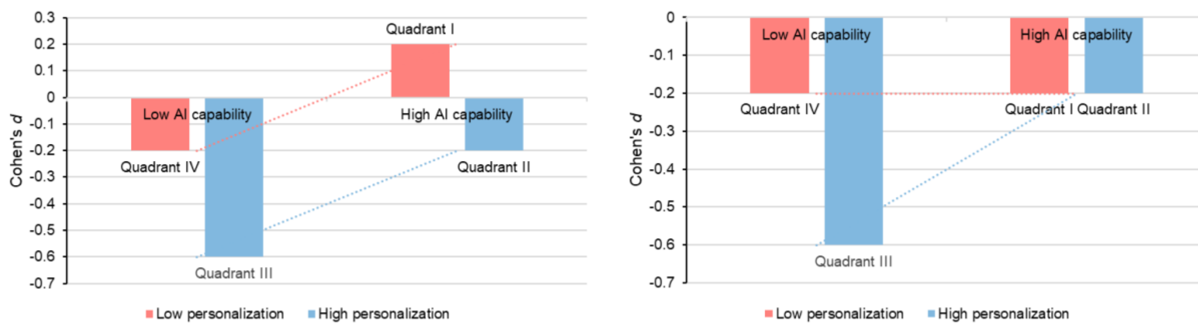
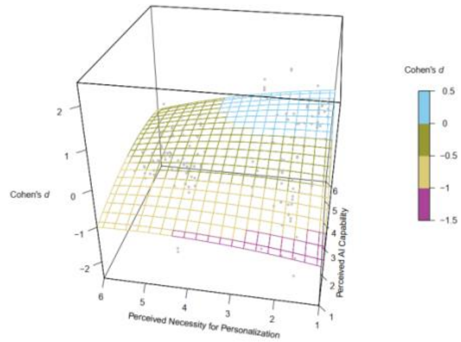


Figure S1a Figure S1b

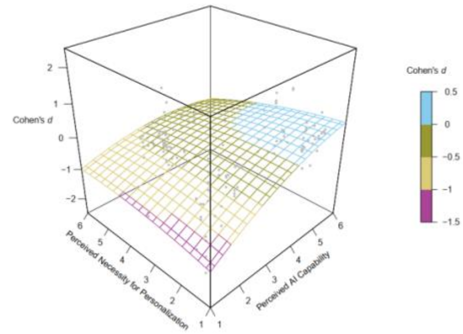
Note. Positive *d* values indicate that participants prefer AI over humans (i.e., AI appreciation), whereas negative *d* values indicate that participants prefer humans over AI (i.e., AI aversion).

Figure S2

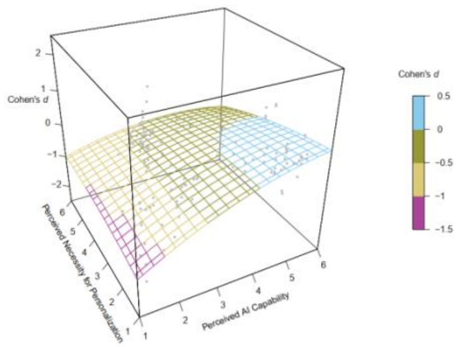
Scatterplots from Other Four Angles Visualizing AI Aversion vs. AI Appreciation as a Function of Perceived AI Capability and Perceived Necessity for Personalization



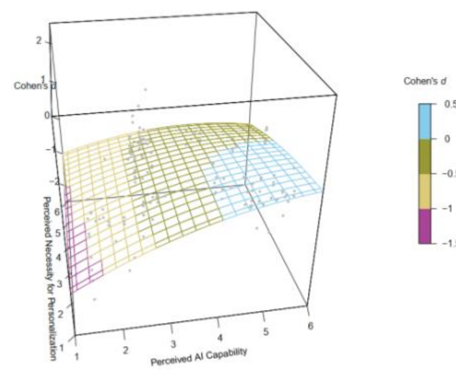
S2a



S2b



S2c



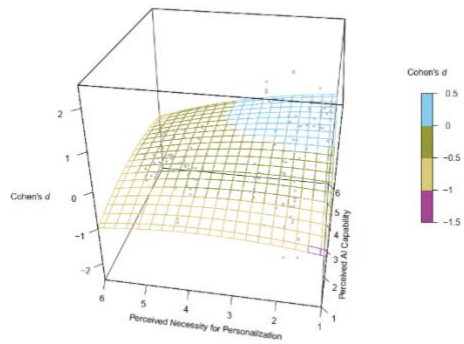
S2d

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).

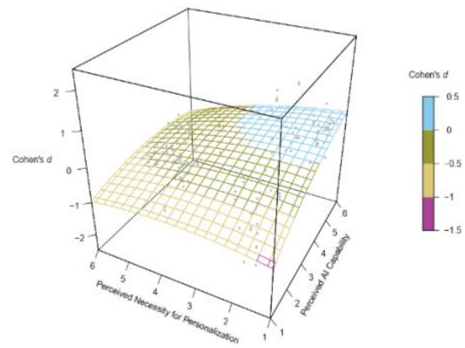
The editorial team noted that since most effect sizes fall within the range of -2.5 to 2.5, it might be excessively precise to present a range of -4 to 4 for the effect sizes. To facilitate visualization, the plot only presents the effect sizes within the range of -2.5 to 2.5 and excludes those outside this range.

Figure S3

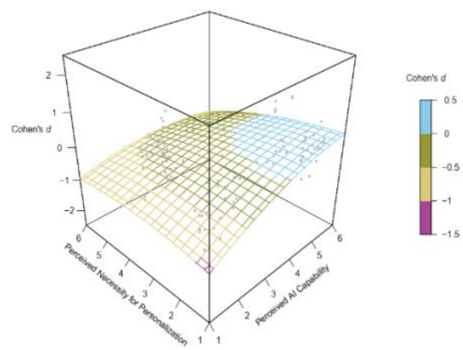
Scatterplots from Five Angles Visualizing AI Aversion vs. AI Appreciation as a Function of Perceived AI Capability and Perceived Necessity for Personalization (After Removing the 8 Outliers)



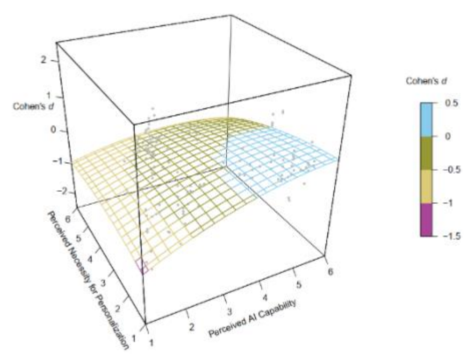
S3a



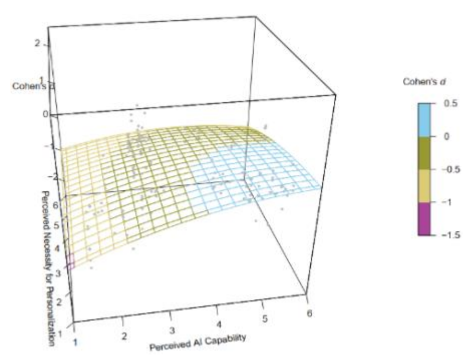
S3b



S3c



S3d



S3e

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 deemed 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.

Separate Publication Bias Analyses for Quadrants II, III, and IV

Quadrant II

First, the contour-enhanced funnel plot in Figure S4a depicts the relationship between effect size and standard error for Quadrant II. Egger's test is not significant (t = -1.63, p = .10), indicating that the funnel plot is symmetric (i.e., a non-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 significantly associated with effect size (b = 0.82, SE = 0.19, p < .001), suggesting that publication bias may exist.

More importantly, to account for statistical dependencies, we conducted a PET-PEESE meta-regression using robust variance estimation (Viechtbauer, 2010). The PET result is not significant (b = -2.23, SE = 1.20, p = .06), suggesting no evidence of publication bias.

Quadrant III

First, the contour-enhanced funnel plot in Figure S4b depicts the relationship between effect size and standard error for Quadrant III. Egger's test is significant (t = 3.08, p = .002), 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 non-reporting 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 significantly associated with effect size (b = -0.83, SE = 0.27, p = .002), suggesting that publication bias may exist.

More importantly, to account for statistical dependencies, we conducted a PET-PEESE meta-regression using robust variance estimation (Viechtbauer, 2010). The PET result is significant (b = 1.88, SE = 0.93, p = .04), so the PEESE estimate is preferred. The PEESE estimate is significant (b = 4.90, SE = 1.98, p = .01), suggesting that publication bias may exist.

Quadrant IV

First, the contour-enhanced funnel plot in Figure S4c depicts the relationship between effect size and standard error for Quadrant IV. Egger's test is not significant (t = 1.92, p = .055), indicating that the funnel plot is symmetric (i.e., a non-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 = 0.59, SE = 0.40, p = .14), suggesting no evidence of publication bias.

More importantly, to account for statistical dependencies, we conducted a PET-PEESE meta-regression using robust variance estimation (Viechtbauer, 2010). The PET result is not significant (b = 2.74, SE = 2.42, p = .26), suggesting no evidence of publication bias.

Figure S4a
Quadrant II Funnel Plot

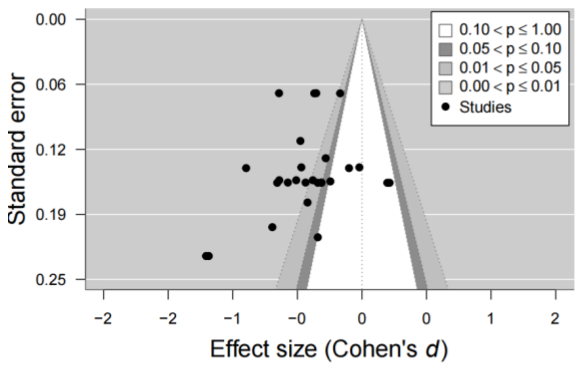


Figure S4b
Quadrant III Funnel Plot

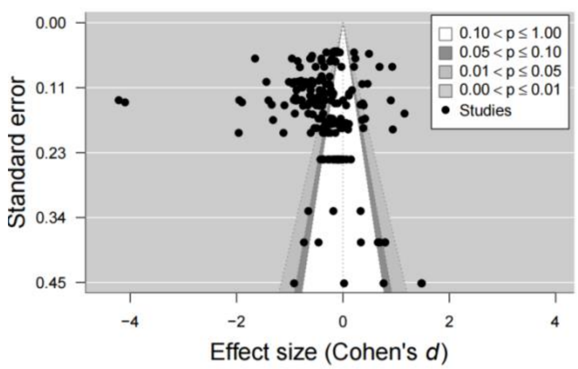


Figure S4c
Quadrant IV Funnel Plot