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Difference in and Influences on Public Opinion About Artificial Intelligence in 20 Economies: Reducing Uncertainty Through Awareness, Knowledge, and Trust

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This study examines how demographics (sex, age, education, religiousness), public (institutional) trust, support for science, science news use, and economy-level differences shape public opinion about artificial intelligence (AI) across and within 20 economies. According to the diffusion of innovations theory, uncertainty about an innovation may be reduced through awareness, knowledge, and trust, influencing opinions about its general social implications. Based on responses from 32,330 adults across 20 economies in a Pew survey, public opinion on whether AI is good for society ranged from 43.4% to 84.5%, with a mean of 65.0%. ANCOVA and binary logistic regressions—explaining the overall variance of 14% and 19%, respectively—show that all proposed influences were significantly associated with AI opinion, though with small effect sizes. The associations between awareness of and trust in institutions and science news with general opinion about AI and society are fairly consistent. The 20 economies explained 5% to 7% of the variance in opinion.

Keywords: artificial intelligence, diffusion of innovations, multieconomy, public trust, science media

In just a few years, artificial intelligence (AI) has pervaded nearly every aspect of people's lives, powering information and communication technologies (ICTs) like smartphones, social media, search engines, e-commerce recommendations, and robotics globally. Livingston and Risse (2019) provide an accessible summary of current and near-term AI applications, including the blending of AI and human intelligence, with concomitant philosophical, moral, and ethical issues, such as the survival of humanity (see also Anderson & Rainie, 2023; Brachman & Levesque, 2022; EU Commission's High-Level Expert Group on AI, 2019; Lennox, 2020; Wang & Siau, 2019). AI can benefit individuals, organizations, and society. However, the nature, applications, and consequences of AI are uncertain. As Coombs, Hislop, Taveva, and Barnard (2020) noted, there are safety and risk concerns about the adoption and use of such innovative

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technologies. Thus, this study examines how the general public in 20 economies considers AI's impact on society and applies a diffusion of innovations approach to assess the influence of awareness, knowledge, and trust on these opinions, both within and across economies. It seeks to answer three general research questions on public opinion about AI: What is the global state of public opinion about AI? What individual, institutional trust, science media, and economic factors are associated with these opinions? Do these factors vary across economies?

Literature Review[1]

Current and Potential AI Concerns

Several widely cited public statements indicate the great risks associated with rapid AI development. For instance, the Center for AI Safety (2023) posted this one-sentence statement: "Mitigating the risk of extinction from AI should be a global priority alongside other societal-scale risks such as pandemics and nuclear war." Similarly, a recent open letter with more than 30,000 signatures claimed that "*Advanced AI could represent a profound change in the history of life on Earth, and should be planned for and managed with commensurate care and resources"* (Future of Life Institute, 2023, p. 1; emphasis in original). Vesnic-Alujevic, Nascimento, and Pólvora (2020) summarized research on many of the societal and ethical implications of AI/machine learning considered in EU policy documents. Many others have discussed and reviewed concerns, ranging from human dignity and privacy to market disruption, unemployment, and regulatory and policy approaches (Anderson, Rainie, & Luchsinger, 2018; EU Commission's High-Level Expert Group on AI, 2019; Federspiel, Mitchell, Asokan, Umana, & McCoy, 2023; Livingston & Risse, 2019; Lozano, Molina, & Gijón, 2021; Morozov, 2023; Salo-Pöntinen & Saariluoma, 2022; Wang & Siau, 2019; West & Allen, 2018; see Note 1). A broad understanding of the opinions on and management of AI must consider individual, institutional, and economy-level influences and not just technical or economic aspects or benefits.

Influences on Public Opinions About AI

Diffusion of Innovations: Reducing Uncertainty Through Awareness, Knowledge, and Trust

According to the diffusion of innovations theory (DoI) (Rogers, 2003, Chapter 5), in the early stages of an innovation's introduction or diffusion, the most critical factor influencing attitudes or opinions about the innovation—and its subsequent adoption or rejection—is uncertainty. Potential adopters (e.g., persons, organizations, or nations) can reduce uncertainty directly through awareness and knowledge, which are primarily gained via communication channels like media (ranging from advertisements to science news), personal experience, and social networks.

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[1] Due to word limits, the following extensive materials are available from https://osf.io/8bxvm/?view_only=30f7721b3b864a9fa13f0d018b9b6f94: definitions and history of AI; a brief review of concerns about AI; and a summary of 27 expert, national, and international surveys or reviews of surveys of opinions about AI from 2017 through 2023.

This uncertainty can also be indirectly reduced through trust. Trust is "...the willingness of a trustor to be vulnerable to a trustee based on past experiences and positive expectations" and thus is directed toward future risk and uncertainty, bridging "the gap between knowing and not knowing" (Fawzi et al., 2021, p. 155). Trust serves as a shortcut when keeping up with rapidly changing technologies, such as AI, is challenging (Yang et al., 2023). As Buskens (2020) notes, "...adoption by people requires a considerable amount of trust in the new product as well as in the producer" (p. 487). Trusted sources possess "benevolence, integrity, competence, and predictability" (Harrison McKnight & Chervany, 2007, p. 2). Trust influences public judgments about benefits and risks, influencing approval or disapproval and adoption or rejection of behaviors or innovations like AI.

Trust can be social or institutional and may relate to specific domains, such as government or news media. *Social trust* is the extent to which we perceive interactions with strangers as involving low risk or vulnerability, developed through interpersonal experiences (Dinesen, 2012; Twenge, Campbell, & Carter, 2014). *Public* or *institutional trust* refers to confidence in positive outcomes from institutions or authorities, influenced by their competence, credibility, fairness, and transparency (Sønderskov & Dinesen, 2016), and is the focus here.

Trust is crucial for understanding opinions about AI, which is highly uncertain because of its newness, the inscrutability of its processes, the unpredictability of and variance in outputs, and the vast range of potential positive and negative consequences (Gerlich, 2023). AI is intangible, with varying levels of user control, so it is difficult for people to develop trust or clear attitudes toward it (Mays, Lei, Giovanetti, & Katz, 2022). "Public perceptions of AI are often shaped either by admiration for its benefits and possibilities, or by uncertainties, potential threats and fears about this opaque and perceived as mysterious technology" (Brauner, Hick, Philipsen, & Ziefle, 2023, p. 1). Thus, trust is a key influence on opinions about and adoption of AI and related technologies (e.g., Beets, Newman, Howell, Bao, & Yang, 2023; Belk, 2017; Chen & Wen, 2021; Coombs et al., 2020; Lozano et al., 2021; Wang & Siau, 2019; Wike & Stokes, 2018).

Demographic Influences

Demographics

DoI research shows that basic demographics affect awareness, knowledge, attitudes, and opinions about innovations, as well as eventual adoption or rejection (Rogers, 2003). For example, there are age (and in some studies, generational) differences in technology adoption and use (e.g., ICT, social media; e.g., Friemel, 2016). Older generations are often left behind by younger ones (Wu, 2022). Mcquater (2017) reported that more than half (57%) of survey participants aged 55 and older, compared with one-third of those aged 18–34, strongly agreed that they prefer human interactions over AI interactions. Furthermore, twice as many respondents aged 18–34 compared with those more than 55 (24%) said AI was improving their lives.

Men and women often differ in their perceptions of ICTs, trust in online shopping, and AI (e.g., Cyr, Gefen, & Walczuch, 2017; Wu, 2022). Women tend to be less knowledgeable about AI development, while men—specifically those with higher education and income—tend to be more supportive of AI development (Franken, Mauritz, & Wattenberg, 2020). Overall, women express more concern than men about AI technologies, such as driverless cars (Gelles-Watnick, 2022).

An analysis of U.S. adults in early 2020 showed that support for AI was positively associated with all measured demographics—being male, younger, White, having higher education, having higher income, holding liberal political ideology, paying attention to science news, trusting scientists, having lower risk perception, and having higher benefit perception (Yang et al., 2023). In contrast, results from a national survey in Spain showed that greater opposition to AI (i.e., the difference between perceived risks and benefits) was associated with being female, older, having a lower income, holding egalitarian views, expressing privacy concerns, and distrusting science (Lobera, Rodríguez, & Torres-Albero, 2020).

Religiousness

Mercer and Trothen (2021) explain that while a religion like Christianity may oppose AI and transhumanism, conservative and liberal Christians have different rationales. Conservatives may be opposed to the associated science and intellectualism, the perceived loss of human integrity and soul, and the challenge to the centrality of God. Moreover, right-wing Christian Conservatives view transhumanism as the apocalyptic and Satanic end of the faithful, humanity, and time. In contrast, liberals may be concerned with the distributive and social injustices and inequalities associated with these technologies. However, both groups may support AI benefits for health and longevity enhancements. In a 2018 U.S. representative sample, average support for developing AI was greater for non-Christian religious affiliations than for Christians (Zhang & Defoe, 2019).

Hindus and Buddhists may be less concerned about AI, given their beliefs in reincarnation, karmic cycles, consciousness, enlightenment, and salvation (Mercer & Trothen, 2021). Ikari et al. (2023) reported that religiosity (beliefs, attendance) and religion-related values (anthropomorphism, animism) in the United States (with a largely Abrahamic religious foundation) and Japan (predominantly Shinto-Buddhist) were differentially associated with valuing moral concern for robots. In the United States, moral care for robots was negatively associated with religiosity and religion-related values, as well as anthropocentrism. In contrast, in Japan, it was positively associated with religiosity, animism, and anthropocentrism. The higher acceptance of robots in Japan compared with other countries is likely influenced by Shinto animism, its lower distinction between nonhumans and humans, and its values on the pervasive presence of nature. Thus, different religions may view AI positively or negatively, depending on its applications. However, in general, the more religious one is, the less uncertainty one might have, thus affecting opinion about AI. Yam, Tan, Jackson, Shariff, and Gray (2023) also discuss religious and other explanations for differences in opinions about robots, algorithms, and AI between Asian and Western populations.

Institutional Influences

Public (Institutional) Trust

Given the uncertain nature, use, and implications of AI, we may rely, to some extent, on our trust in surrounding institutions to help interpret intelligent technologies as primarily "good" or "bad." Under such conditions of limited knowledge, technology users turn to the media, laws, and institutions for explanation and protection (Wong, Tan, Ooi, & Dwivedi, 2023). Public (institutional) trust applies to diverse institutions. National governments are policymakers that support, suppress, or regulate AI development in their economies (Salo-Pöntinen & Saariluoma, 2022; Vesnic-Alujevic et al., 2020). The military is an important institution because of concerns about its use of AI technology as an autonomous weapon; many think it is/would be dangerous and immoral (Belk, 2017). The news media sets the agenda for and frames how scientific news is reported, thus affecting public perceptions of science and technology (Brewer, Bingaman, Paintsil, Wilson, & Dawson, 2022; Weaver, Lively, & Bimber, 2009). Scientists, especially data scientists and software engineers, design and program AI and convey knowledge about and credibility in technology (Lewis, 2024). Finally, business leaders have the power to decide whether and how their organizations will adopt AI in their processes, products, and services (Enholm, Papagiannidis, Mikalef, & Krogstie, 2022; Rossi, 2018), all of which can affect public trust in AI. A survey of more than 17,000 respondents in 17 countries "found a strong association between people's general trust in government, commercial organizations and other institutions and their confidence in these entities to use and govern AI" (Gillespie, Lockey, Curtis, Pool, & Akbari, 2023, p. 4).

Science Support and News

We may also turn to more trusted institutional sources, such as science and media, for news and information. Trust in science is necessary for society to apply evidence-based policies and risk-reduction programs. Lee, Taylor, Ahmed, and Moon (2024) show how using news and social media to obtain social, political, or public affairs information influences this trust.

Support for Science

Two specific forms of institutional trust include perceptions of the general effects of science and whether government investments in science are worthwhile. For example, in China, people who support governmental investments in science tend to hold positive views about AI (Cui & Wu, 2021). A large survey in Spain concluded that "people have a negative attitude if they are not interested in scientific discoveries and technological developments and if AI and robots are not useful at work" (Lozano et al., 2021, p. 1).

Media and Science News

In many societies, news media are a highly trusted source (Van Dalen, 2020), but this trust is fairly volatile (Hanitzsch, Van Dalen, & Steindl, 2018) and is becoming more politically polarized (Barthel & Mitchell, 2017). Considerable research reviews the relationship between news and trust (e.g., Fawzi et al., 2021; Strömbäck et al., 2020). More specifically, media use can affect public perceptions of AI (e.g., Brantner & Saurwein, 2021; Brewer et al., 2022; Crockett, Garratt, Latham, Colyer, & Goltz, 2020; Cui & Wu, 2021; Kelley et al., 2021). Analyzing 1,776 news articles from four major newspapers covering AI in 40 countries, Sun, Zhai, Shen, and Chen (2020) reported that the three most frequently discussed AI-related topics were robots and humanoids, brain and life, and regulation and policy. Overall, benefits were emphasized more than limitations or risks, but the analysis raised the issue of international competition and challenges to the geopolitical landscape.

Economic Influences (see Note 1)

Gerlich (2023) noted a wide variety of potential influences on AI adoption across countries, such as "income distribution, gender roles, developments of financial institutions, crime, competitiveness, economic productivity, work culture, and socio-economic development" (p. 11). Most industrial countries have already developed at least initial national AI strategies (e.g., Salo-Pöntinen & Saariluoma, 2022), but other countries have not. Many Asian countries, especially South Korea and Singapore, have made major strides in the development of AI (Johnson & Tyson, 2020). Fawzi et al. (2021) reported lower trust in North Atlantic, Liberal, and commercial media systems, partially because they foster low-quality journalism and political polarization. Trust in science varies considerably across countries and is associated with many differences in education, institutional confidence, inequality, technology access, religion, ideology, press freedom, economic interests, research funding, and so on (Mehta, Hopf, Krief, & Matlin, 2020).

Results from a survey of more than 10,000 respondents across eight countries showed that people in developed countries have varying feelings, emotions, and needs about AI compared with those in developing countries, shaping how AI is perceived, adopted, and normalized globally (Kelley et al., 2021). For example, people in Japan tend to have positive perceptions about AI and robots (Neri, 2021; because the Japanese population is aging, some elderly people use household robots or healthcare robots). Using data from Lloyd's Register Foundation's 2019 World Risk Poll, which included 154,195 participants from 142 countries, Neudert, Knuutila, and Howard (2020) described how public understanding of AI's risks and benefits varies significantly around the world. Some of these studies have emphasized the importance of reporting public perceptions of AI from a cross-country perspective (e.g., Kelley et al., 2021; Mcquater, 2017; Neudert et al., 2020), but typically only report descriptives and cross-tabulations.

Research Questions

The above review justifies the following research questions.

RQ1: *What are overall and economy-specific public opinions about AI?*

RQ2: *How are (a) demographics, (b) institutional trust, (c) support for science, (d) science news coverage, and (e) economy associated with public opinion about AI, across economies?*

RQ3: *How are (a) demographics, (b) institutional trust, (c) support for science, and (d) science news coverage associated with public opinion about AI, within economies?*

Methods

Sample

The data come from the Pew Research Center's (2020) International Science Survey data; https://www.pewresearch.org/science/dataset/international-science-survey/). This phone survey was administered from December 2019 to March 2020 in 20 economies, including Australia, Brazil, Czech Republic, Canada, France, Germany, India, Italy, Japan, Malaysia, Netherlands, Poland, Russia, Singapore, South Korea, Spain, Sweden, Taiwan, the United Kingdom, and the United States. The resulting sample size is *N* = 32,330 adults.

Measures[2]

Demographics

Sex was coded as 0 = f and 1 = m. *Age* was measured in years. Because the number and types of educational levels varied by economy, the levels were z-scored within each economy, and the resulting z-values were used as the single *education* measure. Two questions asked about the *frequency* of attending religious services, reversed to 1 = never to 6 = more than once a week, and *salience* "How important is religion in your life" (reversed to 1 = not at all important to 4 = very important). These both loaded .91 on a principal component (eigenvalue = 1.65, 82.4% variance explained), and the mean scale achieved a Cronbach's α of .76. Thus, these were each first z-scored overall, and the mean value was used to represent *religiousness*.

Public (Institutional) Trust

Participants were asked: "How much do you trust [randomized institution] to do what is right for [respondent's economy]?" The inserted items were (a) the national government, (b) the military, (c) the news media, (d) scientists, and (e) business leaders. After reverse coding, the choices were as follows: 1 = not at all, 2 = not too much, 3 = some, and 4 = a lot. Principal component factor analysis indicated one dimension, *institutional trust* (eigenvalue = 2.16, 43.2% variance explained), with a Cronbach's α = .67.

Support for Science

Perception about science was measured by the question: "Overall, would you say developments in science have had a mostly positive effect, a mostly negative effect on society or would you say there have been equal positive and negative effects on society?" The choices were recoded and reversed into 1 = mostly

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[2] The authors had no role in the design, administration, or management of the items and data, including selection of the 20 economies. Thus, questions asked in the survey are not standard multi-item scales used in prior research. Following the Pew Research Center protocol, we refer to the 20 entities as "economies" rather than "countries."

negative effect, 2 = equal positive and negative effects, and 3 = mostly positive effect. *Perception about government investments in science* was measured by the question, "In your opinion, are government investments in scientific research aimed at advancing knowledge usually worthwhile for society over time, or are they not worth the investment?" with 0 = no, 1 = yes.

Science News

Media use for science news is measured with the question: "How often do you see, hear or read something in the news about science?" Recoded responses were 1 = never, 2 = rarely, 3 = sometimes, and 4 = often. The question for measuring perception about *news coverage about science* is: "Overall, how would you rate the job news media do in covering science?" Recoded choices were 1 = very bad job, 2 = somewhat bad job, 3 = somewhat good job, and 4 = very good job.

Opinion on AI

The dependent variable of opinion about AI was measured by responses to this question: "Consider all the advantages and disadvantages of the development of artificial intelligence, which are computer systems designed to imitate human behaviors (AI). Overall, would you say this has mostly been GOOD thing or a BAD thing for society?" Responses were coded as 0 = bad thing for society and 1 = good thing for society. The analyzed measure excluded volunteered responses of "both," "neither," "don't know," or "refused" (14.2%).

Results

Descriptives

Table 1 presents the overall descriptive statistics. Fifty-three percent of the respondents were male, with a mean age of 48.5 years. The average frequency of religious service attendance was between seldom and a few times a year (2.8 of 6), while religion was rated as slightly important (2.66 of 4). Education and religiousness values are z-scores (standardized within and across economies, respectively). The mean institutional trust score was 2.74 of 4, specifically ranging from 3.18 for scientists to 2.46 for business leaders. Support for and news about science were all positive, with M = 2.47 (of 3) for perception of science as having a mostly positive effect on society and 88% thinking that government investments in science were worth it. Respondents reported occasional exposure to science news (3.1 of 4) and were neutral about how well the news media covered science. Opinions about AI were somewhat positive (M = .65, SD = .48).

Table 1. Descriptives, Overall.

Variable	*N*	Min	Max	*M*	*SD*
Sex (m = 1)	32,330	0	1	.52	.500
Age	31,891	18	97	48.45	18.116
Education[a]	32,019	–4.01	8.00	.2420	1.524
Religiousness[b]	32,271	–1.43	1.90	.0018	.909
Attend frequency	29,923	1	6	2.80	1.562
Religion importance	32,067	1	4	2.66	1.157
Trust (mean of following:)	28,048	1	4	2.74	.606
Natl govt	31,743	1	4	2.49	1.010
Military	30,989	1	4	3.13	.913
News media	31,550	1	4	2.48	.947
Scientists	30,692	1	4	3.18	.834
Business leaders	30,639	1	4	2.46	.908
Perception of science	31,186	1	3	2.47	.608
Govt invest in science worthwhile	30,296	0	1	.88	.330
Media use for science	31,947	1	4	3.06	.903
News coverage of science	30,471	1	4	2.77	.749
AI Opinion	27,721	0	1	.65	.477

Note. a = z-score within economy; b = z-score across economies.

RQ1: Influences on Public Perceptions About AI

Overall, 65.0% reported that they felt AI was a "somewhat or very good thing" for society. Table 2 summarizes the AI opinion rankings and percentages across the 20 economies. A one-way ANOVA found a significant overall difference across economies, with a small effect size (.067). The economies most positive about AI were India (84.5%), followed by Singapore, Taiwan, South Korea, and Japan (79.0%), while the least positive were France (43.4%), followed by the Czech Republic, Poland, and Germany (54.1%) [3].

[3] A cluster analysis based on the pairwise differences across economies in corrected means of AI opinion from the ANCOVA output identified two sets of economies with a substantial significant difference in mean AI opinion: (1) Italy, Japan, India, Singapore, Sweden, South Korea, and Taiwan (*M* = 78.4%), and (2) Poland, Brazil, Russia, France, Czech Republic, The Netherlands, Canada, Germany, Australia, Malaysia, the United Kingdom, and the United States (*M* = 54.9%), or 43% higher for the first region.

Table 2. Economy Differences in Public Opinion About AI.

	AI Opinion		
Economy	Rank	# Good	% Good
Australia	10	802	58.8
Brazil	14	804	55.4
Canada	11	798	57.0
Czech Republic	19	574	53.0
France	20	544	43.4
Germany	17	743	54.1
India	1	2,135	84.5
Italy	8	884	70.2
Japan	5	971	77.9
Malaysia	15	864	54.3
Netherlands	13	798	56.0
Poland	18	542	53.9
Russia	9	794	63.2
Singapore	2	1,111	82.7
South Korea	4	1,131	78.4
Spain	7	961	73.5
Sweden	6	979	73.5
Taiwan	3	1,101	80.1
United Kingdom	16	722	54.2
United States	12	759	56.3
χ^2 (economy by good/bad)	df(19) = 869.30 ***		
F (economy by good/bad)	F(19,27701) = 105.42 *** η^2 = .067		

N = 27,721; *** p < .001

RQ2 and RQ3: Explanatory Influences Across and Within Economies

Table 3 summarizes the diagnostic ANOVA results for AI opinion, showing significant but small economy-level effects. Because the overall analyses include data from 20 economies and some small cluster effects, it may be necessary to consider robust standard errors (because of heterogeneity in variance in each measure across economies) and cluster robust standard errors (because of differences associated with the economies or second-level influences/random effects in a multilevel modeling approach). McNeish, Stapleton, and Silverman (2017) argue that multilevel modeling (MLM) is unnecessary in many cases, and testing for and correcting cluster robust standard errors is often sufficient. Bryan and Jenkins (2016) summarize alternatives to MLM: (a) a common model applied to pooled data using economies as fixed effects, (b) a common model applied for all economies combined using cluster robust standard errors, and (c) a separate model fitted to the data for each economy (used for testing economy-specific relationships). We apply all three as appropriate to identify cross-economy differences while accounting for within economy shared variance (cluster effects).

Table 3. Diagnostics of Univariate ANOVA Analyses of AI Opinion.

Overall *F*	η_p^2	Adj R^2	Levene test	Hetero-skedasticity *F*	Welch robust means test	ICC	Observed power (at $p < .05$)
$F(19, 27{,}720) = 105.42$ ***	.137	.136	$F(19, 22{,}377) = 158.94$ ***	$F(1, 22{,}395) = 1{,}304.75$ ***	(19, 9843.5) = 118.75 ***	.066	.99–1.00 for all except age (.93) and two economies (.82, .88)

Note. Overall *F* = ANOVA means test; η_p^2 = partial eta^2; adj R^2 = adjusted R^2; Levene = test of homogeneity of variances; Heteroskedasticity F-test via SPSS; Welch = robust errors means test; ICC = intracluster or intraclass coefficient.

We conducted an ANCOVA with economy as a factor, which provided analyzed means and η_p^2 values for each influence while applying HC3 robust standard error correction. Additionally, we also conducted binary logistic regression to obtain odds ratios for the explanatory variables, appropriate processing of the 0,1 dependent variable value, direction of coefficients, and level of prediction accuracy. For both analyses, economy was entered first, with sex, age, education, and religiousness entered in the second block, trust in the third block, and support for science and science news coverage in the fourth.

Table 4 shows that all variables were significantly associated with AI opinion, with a η_p^2 of 13.7%. The single largest source of variance explained was economy (η_p^2 = .050), but the combined individual-level influences explained nearly twice the variance. Economies with the largest individual η_p^2 values for AI were Taiwan (.012), South Korea (.010), and India (.010), indicating that economy-level differences were slightly more salient for those economies. The most influential factors for AI opinion were public perception of science (η_p^2 = .020), trust (.013), and sex (.008).

Table 4. ANCOVA Results Explaining (Positive) AI Opinion
A. Percent "Good for Society," by Economy.

Economy	*N*	*M*	SD
Australia	1,139	.60	.489
Brazil	1,211	.55	.498
Canada	1,152	.59	.492
Czech Republic	893	.55	.498
France	953	.46	.499
Germany	1,127	.57	.495
India	1,694	.83	.373
Italy	956	.71	.453
Japan	982	.79	.410
Malaysia	1,486	.54	.498
Netherlands	1,274	.57	.496
Poland	638	.59	.493

Russia	912	.66	.474
Singapore	999	.83	.378
South Korea	1,270	.79	.408
Spain	1,177	.74	.440
Sweden	1,129	.76	.428
Taiwan	1,179	.81	.390
United Kingdom	1,030	.58	.494
United States	1,210	.57	.495

B. Between-Subjects Effects.

Source	*F*	η_p^2
Corrected model	126.53	.137
Intercept	23.14	.001
Sex	188.88	.008
Age	11.72	.001
Education	94.10	.004
Religiousness	83.24	.004
Trust	299.98	.013
Public perception about science	449.13	.020
Govt invest in science worthwhile	63.14	.003
Media use for science news	19.51	.001
News coverage about science	24.93	.001
Economy	62.60	.050

Note. Uses HC3 robust error correction
N = 22,397; Adjusted R^2 = .136; All p < .001

C. Parameter Estimates.

Explanatory Variables	B	S.E.	*t*	η_p^2
Intercept	–.307	.029	–10.67	.005
Australia	.137	.024	5.71	.001
Brazil	.217	.023	9.31	.004
Canada	.115	.024	4.84	.001
Czech Republic	.081	.025	3.26	.000
France	.073	.025	2.98	.000
Germany	.116	.024	4.86	.001
India	.338	.023	14.94	.010
Italy	.303	.024	12.48	.007
Japan	.302	.024	12.45	.007
Malaysia	.130	.023	5.57	.001
Netherlands	.096	.024	4.07	.001
Poland	.166	.026	6.36	.002
Russia	.206	.025	8.34	.003
Singapore	.319	.024	13.04	.008

South Korea	.351	.023	15.02	.010
Spain	.275	.024	11.47	.006
Sweden	.237	.024	9.87	.004
Taiwan	.384	.023	16.39	.012
United Kingdom	.131	.024	5.42	.001
Sex (m = 1)	.083	.006	13.74	.008
Age	–.001	.000	–3.42	.001
Education	.028	.003	9.70	.004
Religiousness	–.035	.004	–9.12	.004
Trust	.102	.006	17.32	.013
Perception of science	.112	.005	21.19	.020
Govt invest in science worthwhile	.075	.009	7.95	.003
Media use for science	.017	.004	4.42	.001
News coverage of science	.022	.004	4.99	.001

Note. Uses HC3 robust error correction
All $p < .001$, except for France, $p < .005$.

Results from the binary logistic regressions (Table 5) are not directly comparable to the ANCOVA results because the coefficients and odds ratios (Exp(B)) for each dummy-coded economy are relative to the referent economy, in the United States. Economies with the strongest positive associations with AI opinion were Taiwan (7.36), India (6.05), and South Korea (5.96). Of the individual influences on AI, the highest odds ratios were for perception of science (1.72), trust (1.66), and sex (male, 1.53).

Table 5. Results From Binary Logistic Regression on AI Opinion, Overall.

Explanatory Variables	B	S.E.	Wald	Exp(B)
Economy (df = 19)			1,082.19	
Australia	0.67	.119	31.63	1.95
Brazil	1.09	.115	89.49	2.97
Canada	0.56	.118	22.96	1.76
Czech Republic	0.42	.122	11.51	1.51
France	0.42	.120	12.12	1.52
Germany	0.58	.118	23.87	1.78
India	1.80	.120	224.50	6.05
Italy	1.48	.123	143.17	4.38
Japan	1.51	.127	141.52	4.55
Malaysia	0.66	.115	32.81	1.93
Netherlands	0.48	.116	16.73	1.61
Poland	0.82	.128	40.48	2.26
Russia	0.99	.123	65.46	2.70
Singapore	1.69	.132	163.51	5.42
South Korea	1.78	.122	213.50	5.96
Spain	1.35	.122	121.19	3.84

Sweden	1.17	.124	89.14	3.22
Taiwan	2.00	.125	254.14	7.36
United Kingdom	0.65	.119	29.56	1.91
Sex (m = 1)	0.43	.031	188.24	1.53
Age	0.00	.001	10.067	1.00
Education	0.14	.015	90.21	1.15
Religiousness	–0.18	.020	79.53	0.84
Trust	0.51	.030	280.86	1.66
Perception of science	0.54	.027	420.50	1.72
Govt science worth invest	0.33	.046	50.38	1.39
Media use for science	0.09	.019	19.48	1.09
News coverage of science	0.11	.023	25.06	1.12
Constant	–4.03	.150	723.38	0.02
N			22,397	
χ^2 (4)			619.01	
-2 Log likelihood			25,502.93	
Nagelkerke R^2			.186	
Percentage correct			70.2	

Note. United States is a referent economy.
All $p < .001$, except age, $p < .05$

Table 6 provides summary results from binary logistic regressions for each economy about AI opinions. Because of smaller sample sizes in each economy, not all influences were significant across all economies. The variables with the highest mean odds ratio and the largest number of significant influences across economies, respectively, were perception of science (1.79, 19) and trust (1.75, 17), followed by sex (1.54, 13), education (1.16, 11), and religiousness (.86, 11). Economies with the greatest Nagelkerke R^2 (more explained variance in AI opinion) are Australia (.217), Canada (.205), the United Kingdom (.193), and the United States (.190); the two lowest are India (.06) and Malaysia (.066). Overall classification prediction accuracy was 70.2%, with economy-specific values ranging from 59.8% (Malaysia) to 83.4% (India).

Table 6. Results From Binary Logistic Regressions for AI Opinion, by Economy.

Economy	Sex (M)	Age	Educ	Relig	Trust	Percept science	Govt science worth invest	Media use for science	News coverage science	Const	χ^2 (4,9)	Nag. R^2	*N*	Class. predict acc.
Australia	1.51**	0.99**	1.42***	0.90	2.11***	2.10***	1.86*	1.18*	1.09	.01***	198.6***	.217	1,139	68.4
Brazil	1.65	0.99	0.92	0.83*	1.40***	1.36**	1.31	1.10	1.28**	.10***	89.8***	.096	1,210	60.4
Canada	1.75***	1.00	1.37***	0.84	1.65***	2.27***	1.48	1.07	1.28	.01***	189.6***	.205	1,150	67.3
Czech Republic	1.65***	0.99**	1.12	0.75**	2.06***	1.63***	1.48	0.99	1.43**	.01***	104.3***	.147	893	64.7
France	1.79***	1.00	1.24**	0.91	2.27***	1.49**	1.25	1.01	0.98	.03***	121.1**	.16	953	64.2
Germany	1.24	1.00	1.10	0.72***	1.77***	1.68***	1.34	1.06	1.25*	.02***	123.9***	.14	1,126	64.7
India	0.99	1.00	0.86*	0.96	1.18	1.45***	2.24***	0.98	1.16	.52	61.1***	.06	1,693	83.4
Italy	1.57**	1.00	1.13	0.81*	1.69**	1.98	0.94	1.09	1.09	.06***	69.7***	.101	956	70.2
Japan	1.36	0.99*	1.40***	1.19	2.81***	1.67***	1.45	1.07	0.97	.06***	99.6***	.149	982	79.4
Malaysia	1.75***	1.02***	1.15*	0.65***	1.42***	1.21*	1.31	1.01	1.06	.12***	75.4***	.066	1,486	59.8
Netherlands	1.51***	1.00	1.24***	0.83**	2.18***	1.55***	1.46*	1.08	1.01	.02***	175.9***	.173	1,273	65.8
Poland	1.49*	0.99*	1.10	0.71**	1.66**	1.40**	1.55	1.13	1.31	.06***	57.4***	.117	634	65.5
Russia	1.34	0.99	1.05	0.80*	1.76***	1.63***	3.73***	1.15	0.93	.03***	97.9***	.141	911	69.6
Singapore	1.42	0.99	0.98	0.95	1.80	1.89	1.51	1.03	1.48	.04	63.6	.103	999	82.4

	*				***	***			**	***	***			
South Korea	1.91***	1.00	1.07	0.77***	1.25	1.76***	1.87**	1.28*	1.18	.07***	114.6***	.134	1,269	78.6
Spain	1.74***	1.01	1.33***	1.03	1.32*	2.09***	1.53	1.11	0.96	.06***	96.1***	.115	1,176	74.3
Sweden	1.31	0.99	1.14	0.80*	1.78***	2.46***	0.88	1.48***	0.85	.03***	123.9***	.115	1,129	76.9
Taiwan	1.22	1.01	1.19*	0.83	1.24	2.08***	0.93	1.18	1.08	.17***	60.2***	.08	1,179	81.0
United Kingdom	1.75***	0.99**	1.34***	0.97	1.93***	2.04***	1.07	1.03	1.15	.03***	159.3***	.193	1,030	66.4
United States	1.83***	1.00	1.12***	0.85*	1.71***	2.14***	1.20	1.10	1.24**	.01***	183.9	.190	1,209	66.6
M Exp(B) odds ratio	1.54	1.00	1.16	0.86	1.75	1.79	1.52	1.11	1.14	–	–	–	–	–
# Sign. influences	13	6	11	11	17	19	4	3	5	–	–	–	–	–

Note. Values are Exp(B) odds ratios for each variable in each separate economy binary logistic regression.
* p <.05, ** p < .01, *** p < .001

Discussion

Overall, emphasizing the DoI principle of reducing uncertainty about an innovation through awareness, knowledge, and trust (Rogers, 2003), the analyses support an association between AI opinion and demographics, public (institutional) trust, science media use, and economy.

The results for levels of AI opinion are consistent with some of the above-reviewed studies (Neri, 2021; Neudert et al., 2020; Wike & Stokes, 2018), except for the lower percentage of positive opinions in some countries, as reported by Kelley et al. (2021). Sex (male) is positively associated with AI opinion, consistent with several previous studies (e.g., Franken et al., 2020; Gelles-Watnick, 2022). While age has slightly varying associations with AI within and across the MANCOVA and binary logistic regressions, it essentially explains no variance, hovering around 0. This differs from Mcquater's (2017) findings that younger adults tend to view AI more positively than older adults. As also found in the DoI literature, education is positively associated with technology perception, and, here, with AI opinion. Perhaps because of beliefs about the appropriate relationship between humans and machines, greater religiousness is negatively related to AI opinions.

The result that public trust is a significant predictor of considering AI as beneficial for society supports previous studies (e.g., Belk, 2017; Coombs et al., 2020; Crockett et al., 2020). As noted, though, trust in particular public institutions varies, so the overall trust scale hides the separate effects to some extent. For example, trust in business leaders had the strongest influence on AI, while trust in the military was not associated with AI opinion. The finding that participants' perceptions of media use and coverage of science news are significant positive predictors of AI opinion complements previous studies, except that science news coverage itself was not significantly associated with AI (e.g., Brantner & Saurwein, 2021; Cui & Wu, 2021; Kelley et al., 2021). The data for this study were collected from 20 economies where media control by governments varies. Thus, media coverage of AI will differ, with varying emphasis on both positive and negative aspects (e.g., ethical issues, risks, and responsibilities) across these economies.

Conclusion

Contributions

By analyzing survey data collected from 20 different economies, this study has provided additional insights into research on opinions about AI, providing several theoretical, methodological, and practical implications.

First, the results support the relevance of awareness, knowledge, and trust in the DoI framework, finding that almost all the influences were significantly associated with opinions about AI. Additionally, the study extends DoI theory by highlighting how institutional trust can influence opinions about an innovation by reducing uncertainty in the adoption process. While DoI explicitly proposes attitudinal (e.g., innovation attributes), media (mass and digital), and social (social networks, opinion leaders, and culture) influences on opinions (and thus subsequent adoption decisions) about an innovation, it does not say much about perceptions of institutional trust, nor does it specifically consider the role of trust in and exposure to science communication. Therefore, we encourage more attention to uncertainty, trust, and science news in future DoI studies, particularly about AI, given the obscure nature and processes of this transformational technology.

Second, this study offers methodological contributions by applying several appropriate multivariate analyses. Previous studies about public perceptions of AI tend to rely on descriptives, cross-tabulations, and correlations (e.g., Kelley et al., 2021; Wike & Stokes, 2018; see Note 1 about survey summaries).

Third, while there is considerable variation in mean AI opinion across the economies (represented by two clusters; see Note 3), the influences are fairly consistent across the 20 economies, with some variation, indicating a common set of (slight) influences of institutional trust and science news exposure across a very diverse set of economies. AI is a global innovation, and fittingly, this study's set of influences seems to be largely global as well. Thus, publicity, policies, and preferences may be tailored for the two international regions.

Fourth, the results of this study have practical implications. For example, public trust, support for science, and exposure to science news have significant associations with opinions about AI. Thus, it is important for institutions, including schools (which can promote science learning in general and about AI in particular), to provide sufficient and transparent information about what AI is and how it will be regulated and used to improve understanding and reduce uncertainty about both the benefits and risks of these new technologies. Our results recommend including discussions about trusted institutional and media sources for AI knowledge, with perhaps slightly different foci for male and female students, consistent with Tables 4C and 5, and slightly different emphases in the two global regions (Note 3). For example, among the already large number of studies on AI and education, Yang (2022) advocates integrating AI awareness and knowledge into middle school science curricula.

Limitations and Suggestions for Future Studies

Although there are significant contributions, this study has some limitations. First, although the data were collected in 20 economies across three continents, future studies may expand this range by surveying participants in Africa, the Middle East, and South America. Another extension of this study would be to integrate relevant economy-level measures (e.g., Internet and mobile phone use, as provided by the International Telecommunications Union) with individual survey responses for a comprehensive multilevel model analysis.

Second, the analyses are quantitative. Other studies can use qualitative research methods to explore public perceptions of AI in a cross-economy context. For example, studies may interview participants across different cultures to obtain more details about the perceived risks of AI, as DoI theory and studies document substantial influences of social and cultural values on innovation adoption (Rogers, 2003). In addition, future studies may interview participants in different economies to explore how well they think the media report AI-related news. Future studies may also interview government officials in different economies for their insights into how to establish policies to guide and regulate AI development, extending Vesnic-Alujevic et al.'s (2020) thematic analysis of EU AI policy documents to enhance public trust and reduce uncertainty.

Third, many other individual-level variables are likely to influence AI opinions but were not included in the Pew survey. One candidate is political ideology. Political ideology and partisanship are associated with opinions about AI (Nam, 2019; Rainie, Funk, Anderson, & Tyson, 2022). A U.S. representative sample in 2020 found that conservatives are more negative about the social effects of central technology corporations, but less supportive of regulation of those same companies than Democrats (Yang et al., 2023). Liberals reported more positive trust in scientists but less trust in technology companies and were more supportive of AI than were conservatives. However, it is unclear what "ideology" means in countries with different cultural, governmental, political, religious, and media structures.

Fourth, future studies may use text-analytic tools to analyze how AI news is reported in different types of media (e.g., newspapers, magazines, and social media) across different economies, similar to the extensive analysis by Sun et al. (2020) on media coverage of AI. Finally, technology can develop, change, and diffuse rapidly. For example, ChatGPT was released by OpenAI on November 30, 2022, and by January 2023, there were an estimated 100 million active users (Hu, 2023). Thus, opinions about AI may evolve quickly with such a pervasive and easy-to-use AI tool, requiring trend analyses or comprehensive time-ordered reviews.

In conclusion, AI holds the potential for both positive and negative transformations in homes, workplaces, societies, and within and across economies. Researchers, designers, vendors, policymakers, and the general public must make informed choices about this technological future, even as it evolves rapidly.

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