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Impacts of Attitudes Toward Government and Corporations on Public Trust in Artificial Intelligence

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ABSTRACT
Artificial intelligence (AI) has alarmed the society of Taiwan believing it is responsible for potential surveillance, data theft and abuse, and other privacy infringements. By adopting the theory of motivated reasoning, this study explores how Taiwanese people's perceptions of AI are affected by their institutional trust, attitudes toward the government and corporations, which are the two most common sponsors of scientific development. First, findings establish that respondents' science trust in AI is made up of perceptions of AI and its science community, and they have lower faith in the AI science community than in AI alone. Second, the perceptions of both AI and its science community are positively associated with trust in government and corporations. Third, scientific news has a direct bearing on AI trust, but not on either government or corporation trust. By contrast, political news has no effect on either trust in AI or its science community, yet trust in government and corporations mediates the influence of political news on trust in AI and its science community. Finally, demographic variables hardly predict trust in AI, AI science community, government, and corporations, but education and gender are directly related to news consumption, which further influences institutional and science trust.

KEYWORDS
Motivated reasoning; news consumption; science community; political orientations; sponsors of scientific research

Public concern over artificial intelligence (AI) usage is rising, as Su (2019) indicates one of the Taiwanese people's primary fears is that it will exacerbate surveillance of citizens, help suppress labor unions, and massively replace the economy's main workforce with robots. Concern over abusive AI applications is not merely associated with corporations, but also with the government. As the Taiwan government is planning on applying AI for broader purposes (e.g., facial recognition, digital identification combined with health care), rumors, particularly among the elderly, abound that the government will utilize AI against dissidents. Public fear over emerging AI technologies in Taiwan is not confined to conspiracies about the government and corporations; people are also worried that scientific experts are not sufficiently exposing any possible perils, owing to the fact that their research projects are largely funded by either corporations or the government; the endowments could basically inhibit them from fulfilling their responsibility as scientists to adequately inform the public. (Figure 1)

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In spite of years of effort and tenable evidence publicized in support of the government's future policies to develop AI, public opinion appears unconvinced of the scientific facts presented by the government, corporations, and science community. As AI is an inexorable technology that governments around the world are dedicated to applying and popularizing, people's resistance to it out of skepticism of social institutions and the belief in anti-government misinformation will very likely become a global phenomenon.

This social disjuncture of trust prompts us to ponder two aspects: the public's incongruent attitudes toward AI as a technology and the AI science community that develops it, and the relationship between the acceptance of AI, consumption of information, and public trust in government and corporations. One can imagine that even if AI development is approaching maturity, when people's skepticism of the discipline and integrity of government, private sectors, and science community remains high and unaddressed, then public distrust of AI will not diminish, because the masses would be constantly agitated over potential abuse of it by those social institutions in power.

There has also been much research shedding light on the increasing public trust in AI by through transparent policies and building a bottom-up and top-down two-way communication in an organization by initiating AI robots and automation (Camporesi et al., 2017; Hengstler et al., 2016; Hmielowski et al., 2014). Nonetheless, studies discussing perceptions of AI in association with public confidence in powerful social institutions like the government and corporations are still relatively limited. As a result, this study aims to advance the literature on this topic and look into the social disjuncture by characterizing a) what constitutes people's science trust in AI; b) how science trust in AI is affected by their institutional trust in government and corporations endowed with developing AI; c) how the consumption of different news types shapes people's attitudes toward government, corporations, as well as AI; and d) what is the role of demographic variables in formulating institutional trust and AI perceptions.

Approaching AI from the Perspective of HMC Research

AI research and communication studies have for a long time been on separate paths. The former centers on how to replicate human intellectual activities and be human-like, whereas the latter concentrates on characterizing the process of messages circulating among the masses and how such circulation is mediated and facilitated by technologies (Lewis et al., 2019; Spence, 2019). With tremendous recent breakthroughs in AI arising from big data, machine learning, natural language processing, and so forth, AI and communication studies are converging in certain aspects as communication with AI becomes a greater part of people's daily routines (Carlson, 2015; Peter & Kühne, 2018; Reeves, 2016), such as talking to Apple Siri for managing smartphone usage, administering privacy among interconnected smart devices, and consuming news produced by AI programs.

Communication studies are still confronted by a challenge: "AI and people's interactions with it do not fit neatly into paradigms of communication theory that for more than a century formed around how people communicate with other people" using media as channels (Guzman & Lewis, 2020, p. 2). As a communicative technology, AI serves as a quasi-human partner with which people communicate information, parting from other media's long-standing role as the channels via which people convey information. Like communicators, AI technologies come in multiple forms and vary from other media

(Ferrara et al., 2016; Graefe et al., 2018). For example, social bots reply to people's comments depending on the contexts in the comments. Automation enables robots to discourse on data and write stories extremely close to human-produced narratives. Virtual assistance converses with people spontaneously. Unlike interactions with other media that are relatively static, AI, by being capable of learning from its human partners, accommodates the ways it responds to people's requests and behaviors.

Conventional communication research assumes in the course of message exchanges that humanity is the communicator with technology functioning as the medium. This assumption forms the foundation for the anthropocentric perspective, which is at variance with the fact that AI technologies are communicative partners with which humanity creates meaning rather than with which humanity creates meaning (Graefe et al., 2018; Gunkel, 2012). Consequently, some researchers in human-machine communication (HMC) advocate that research attention be brought to AI capability of recognizing and reacting to human social cues, and that scholarship should acknowledge that the role of AI in the human society has transited from a channel to a communicator (Guzman, 2019).

How should research approach AI devices as a communicator? Lewis et al. (2019) suggest HMC studies bring attention to the meaning yielded in the masses' interactions with AI and how people interpret these interactions. For instance, the results of Edwards et al. (2016) point out AI device users tend to perceive robots as social instead of mechanical. Gulrez and Neftimeziani (2015) demonstrate that people from time to time seek social connections in technology and that AI robots do show social presence and provide users with a sense of companionship, albeit weak at giving emotional support. There are also studies dedicated to conceptualizing AI as communicative subjects, experimenting on people's acclimation to AI assistants, and investigating potential impacts AI can cause to the existing social structure (Peter & Kühne, 2018; Rosenthal-von der Pütten et al., 2019; Sandry, 2015).

Our research is not arguing that technologies have ceased to mediate communication. What we believe more imperative is that AI technologies have grown beyond the role as communication mediators and that looking into their functions in relation to people's social values as well as perceptions of AI can help open up more in-depth discussions for HMC studies (Dörr, 2016). Hence, in line with Guzman and Lewis (2020), we propose HCM research to focus on the relational aspect of communicative AI – that is, communication via which humans build relationships with each other, and from which they eventually develop social codes and the world. Individuals' communications with each other and with the world vary from society to society, depending on the local cultural contexts and codes. When AI technologies equipped with the unprecedented "quasi-human" attributes enter human society (Carlson, 2015; Guzman, 2019), the foremost question is how AI takes a role in society and how that role assigned by humanity is associated with people's interpretations of AI in relation to themselves.

Social role assignment and assumed relationships are embedded in technology design. For example, AI-based voice assistants are often installed with extraverted female voices (Chang et al., 2018). Suchman (2009) contends that the design of voice assistants with excessive gender cues is reflective of stereotypes attached to human assistants in real life, believing the significance of embedding social roles in technology design is to formulate mental guidance that can inform the masses of how they are supposed to react and interact with AI (Guzman, 2019; Lewis & Westlund, 2015). The design of virtual assistants mainly featuring extraverted female voices is an extension of the social power structure in reality where females are posited by default to be those compliantly following and implementing commands (Chang et al., 2018). With AI being more incorporated into humanity's everyday life, it is increasingly crucial for HMC research to explore the social positioning of this human-like entity (Boyd & Holton, 2018), including what attributes of it contribute to its incorporation and what properties of it distance humanity from it, as well as how the understandings and conceptualizations of the attributes reflect humanity's social values (Jones, 2014; Noble, 2018; Papacharissi, 2019; Primo & Zago, 2015). Positing that public interpretations of AI are derivatives of the masses' perceptions of government, science community, and corporations navigating AI development, this study looks to verify the relationships by means of the motivated-reasoning theory.

Institutional Trust

Described as "willingness to believe, endorse, and enact expert advice," institutional trust is usually a common goal of governments endeavoring to involve the public so that their policies can win better support (Camporesi et al., 2017, p. 25). Giddens (1991) states institutional trust is the essential foundation for the relationship and interaction between laypeople and experts/authority.

According to the H1N1 pandemic survey in the U.S. conducted in 2009, public trust was measured by the competency, honesty, openness, commitment, concern, and care for citizens' best interests by the government and related experts (Freimuth et al., 2013). The survey points out that participants with relatively little trust were apt not to abide by the pandemic prevention instructions despite the instructions being scientifically valid. This discovery suggests that institutional trust is innately fluid, depending on the complexity of issues, approachability of expert knowledge, and intensity of being threatened. As a result, the notion that there is a certain level of categorical public trust for societies to attain is unrealistic. The operation of politics is embedded into the intricate relationships between laypeople, scientific professionals, and the government; institutional trust is subject to the dynamics of social relations.

Nisbet et al. (2015) advocate the theory of motivated reasoning that proposes people tend to make conclusions by biasedly selecting and trusting things that square with their previously held viewpoints and political beliefs in particular. When facing controversial issues, people barely assess the relevant facts and evidence rationally. On the contrary, their inherent political beliefs influence how they interpret new information through "selective exposure, attention, comprehension, and recall" (Taber et al., 2009).

There are two existing primary theories accounting for why equally informed laypeople would approach and interpret scientific evidence in dramatically disparate directions pulled by their political orientations. The intrinsic thesis maintains that political conservatives are fundamentally prejudiced against scientific communities. Certain scholarships assert the bias is largely psychological, which leads conservatives to discount science "via the use of motivated reasoning to shape value-inconsistent information so that the information conforms to preexisting beliefs" (Nisbet et al., 2015, p. 39), whereas liberals are thought of as less apt to employ heuristic information processing when confronted by scientific claims incongruent with their political ideology. Nam et al. (2013) argue that conservatives are driven by a mental mechanism, dogmatism, to shun dissonant-arousing news and tasks and that they also have a tendency toward closure, "creating stark differences in how members of these groups form attitudes and process information about science" (Nisbet et al., 2015, p. 39).

Nonetheless, the intrinsic thesis is attacked by empirical studies on its flaws (Kahan et al., 2012). Kahan's experiment (2013) suggests conservatives do not engage in less systematic processing than liberals. Through manipulating science types and analyzing subjects' political ideologies in relation to trust in scientists participating in policymaking, McCright et al. (2013) reveal that conservatives neither view science as homogeneous nor deny it recklessly by any means. In fact, they principally resist and oppose scientists and projects that challenge modern societies' accomplishments, specifically in the fields of environmental technology and public health. On the other hand, their findings demonstrate that liberals have trouble trusting chemical, industrial, and food sciences. In sum, both conservatives and liberals doubt science, and they prefer to trust some types of science while distrusting of others.

The other theory, the contextual thesis, explains the aforementioned findings in refuting the intrinsic thesis claiming conservatives are innately less able to evaluate scientific statements with reason. The contextual thesis proposes it is not science itself, but how science is employed to greatly uphold policymaking colliding with individuals' identity, values, or interests, that repels conservatives. Both conservatives and liberals are threatened by specific areas of science. For conservatives, they discount "impact science," which focuses on proving how cutting-edge technologies are instead holding societies and human beings back. On the other hand, for liberals, they distrust "production science" that is dedicated to maximizing and optimizing the generation and output of industrial products maintaining people's modern lifestyle. When it comes to biases, both sides exhibit signs of motivated reasoning that enables them to only accept information in harmony with their long-held values when confronted by value-inconsistent news and statements. In other words, political orientations indeed have bearing on public trust in science and governmental policymaking, not owing to the right being more incapable of objectively comprehending new information than the left (or vice versa), but instead due to the cognitive bias witnessed in both of them to belittle scientific statements of little compatibility with their long-standing worldviews; denialism of science is peculiar to neither side. Grounded on the aforementioned literature, we present the following hypotheses.

H1: Government trust is positively associated with a) AI trust and b) AI science community trust.

H2: Corporation trust is positively associated with a) AI trust and b) AI science community trust.

Media and News Effects on Science Trust

Because the public in general has limited knowledge of scientific issues such as genetically modified organisms, climate change, and fracking, Gauchat (2012) argues that people tend to judge a science team's or an institute's trustworthiness by identifying the compatibility of their values, instead of the scientific facts or developments they have yielded. To understand those values, the public usually has to count on media coverage, because most of the time the media do not simply report scientific outcomes and disputes, but also frame scientific topics and the associated researchers, in order to emphasize their positions (as media) in the scientific controversies and to bring more public attention to the little noticed ethical and legal conundrums (e.g., human clones, surrogacy, homosexual gene identification, etc.). At the same time, "the media sources preferred by liberals and conservatives play a role in shaping their respective levels of trust toward scientists . . ., likely due to their heightened attention to in-group messaging" (Hmielowski et al., 2014, p. 869).

In spite of the media acting as a bridge through which the public can approach science teams and get to know something about them as well as their research, the divide between ideology and trust is increasingly being widened along the way from the beginning when the media report science and simultaneously frame stories in accordance with their ideological stances, to audiences selecting the preferred media aligned with their ideology to access scientific issues, and finally to the end where audiences decide whether the scientists and the science are trustworthy by judging if they recognize their values through the lens of media (Dunlap & McCright, 2011; Feldman et al., 2012; Leiserowitz et al., 2010). Media effects on public perceptions of science are salient; scientists' scandals intensively conveyed by the media or excessive stress placed on the downsides of certain sciences placed by media could be a heavy blow to public trust in science (Anderson et al., 2011; Krosnick & MacInnis, 2010). Based on the literature discussed above, we offer the following research questions.

RQ1: Does attention to general news affect government trust, corporation trust, AI trust, and AI science community trust?

RQ2: Does attention to political news affect government trust, corporation trust, AI trust, and AI science community trust?

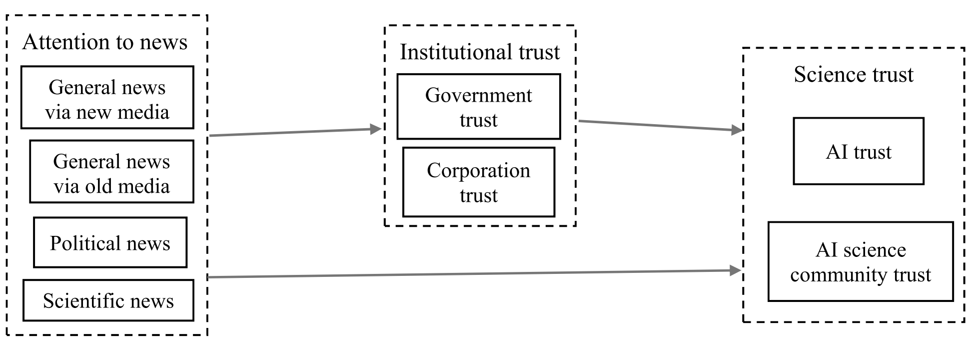

Figure 1. Research model.

RQ3: Does attention to scientific news affect government trust, corporation trust, AI trust, and AI science community trust?

Methods

Our survey was disseminated online between April 29 and May 17 in 2019. Participants were mainly recruited from Dcard (Taiwan's largest online forum for college students) and Facebook. In total, 1,398 feedbacks were collected. After deducting unfinished and unqualified feedbacks, the number of valid feedbacks amounted to 1,009. Among them, 52% are females and 48% are males. The average age is 28 (median = 27, sd = 8.35). As to education, 49% have a bachelor's degree, 25% have a master's or doctoral degree, and 23% have a senior high school diploma. In terms of marital status, 83% are not married, 14% are married, and 2.38% live with their partners without being married. When it comes to employment, 47% work full time, 41% are full-time students, 6% are job seekers, and 3% work part-time. The average monthly family income is NT$70,001–80,000 (median income = NT$60,001–-70,000, sd = 5.45). For residency, 84.73% live in municipalities or in one of Taiwan's major cities (New Taipei, 20.81%; Kaohsiung, 19.43%; Taipei, Taiwan's capital, 18.43%; Taichung, 11.50%; Taoyuan, 7.33%; Tainan, 7.23%), with the remaining 15.27% living in non-municipalities. Up until the survey, approximately 60% agreed that they had given much thought to AI-related issues, whereas just 11.3% disagreed (mean = 3.65, median = 4, sd = .94).

Key Variables

Attention to general news: Seven items (questions 1 to 7) were provided for participants to answer how frequently they watched news in general and were not limited to a specific topic via the following platforms: TV news, print news, websites of TV news, online news, Facebook, LINE, and YouTube. Each question was asked on a 5-point Likert scale (1 = never, 2 = seldom, 3 = average, 4 = sometimes, 5 = often). Results of principal component factor analysis with varimax rotation revealed that questions 3 to 6 formed an index of *attention to general news via Internet media* (eigenvalue = 2.46, 40.99% of variance; α = .68, mean = 3.43, median = 3.5, sd = .91) and that questions 1 and 2 were grouped in another index of *attention to general news via conventional media* (eigenvalue = 1.18, 19.72% of variance; α = .62, mean = 2.59, median = 2.5, sd = 1.07).

Attention to political news: Seven items (questions 8 to 14) were provided for participants to answer how frequently they watched political news through the following platforms: TV news, print news, websites of TV news, online news, Facebook, LINE, and YouTube. Each question was asked on a 5-point Likert scale (1 = never, 2 = seldom, 3 = average, 4 = sometimes, 5 = often). Results of principal component factor analysis with varimax rotation suggested the seven items constituted an index of *attention to political news* (eigenvalue = 3.42, 48.88% of variance; α = .82, mean = 2.86, median = 2.86, sd = .82).

Attention to scientific news: Seven items (questions 15 to 21) were provided for participants to answer how frequently they watched political/scientific news via the following platforms: TV news, print news, websites of TV news, online news, Facebook, LINE, and YouTube. Each question was asked on a 5-point Likert scale (1 = never, 2 = seldom, 3 =

average, 4 = sometimes, 5 = often). Results of principal component factor analysis with varimax rotation suggested the seven items were grouped in an index of *attention to scientific news* (eigenvalue = 3.41, 48.64% of variance; α = .82, mean = 2.94, median = 3.00, sd = .84).

Science trust: Seven items (questions 29 to 35) were borrowed from the government and science trust research of Pechar et al. (2018), and each item was measured by a 5-point Likert scale from "strongly disagree" to "strongly agree." Outcomes of principal component factor analysis with varimax rotation indicated that questions 29 to 31 formed an index of *AI trust* (eigenvalue = 2.34, 46.83% of variance; α = .71, mean = 3.38, median = 3.33, sd = .71), and that questions 32 and 33 formed another index, *AI science community trust* (eigenvalue = 1.10, 22.05% of variance; α = .67, mean = 2.40, median = 2.50, sd = .82). Questions 34 and 35 were removed due to cross loadings.

29. I have very little confidence in the AI science community. (reverse coded)
30. Information from the AI science community is trustworthy.
31. I trust the AI science community to do what is right.
32. The AI science community has too much power and influence in society. (reverse coded) 33. The findings of AI scientists are influenced by who pays them. (reverse coded)
34. The AI science community often does not tell the public the truth. (reverse coded)
35. I am suspicious of the AI science community. (reverse coded)

Government trust: Seven items (questions 36 to 42) were adopted from Pechar et al. (2018), and each item was measured by a 5-point Likert scale from "strongly disagree" to "strongly agree." Outcomes of principal component factor analysis with varimax rotation demonstrated that the seven items formed an index of *government trust* (eigenvalue = 3.89, 55.63% of variance; α = .86, mean = 2.53, median = 2.57, sd = .68).

36. I have very little confidence in government. (reverse coded)
37. Information from government is trustworthy.
38. I trust government to do what is right.
39. Government has too much power and influence in society. (reverse coded)
40. Government looks out for my interests.
41. Government often does not tell the public the truth. (reverse coded)
42. I am suspicious of government. (reverse coded)

Corporation trust: Seven items (questions 43 to 49) were adopted from Pechar et al. (2018). Each item was measured by a 5-point Likert scale from "strongly disagree" to "strongly agree." Outcomes of principal component factor analysis with varimax rotation demonstrated that the seven items constituted an index of *corporation trust* (eigenvalue = 3.49, 49.79% of variance; α = .83, mean = 2.35, median = 2.43, sd = .57).

43. I have very little confidence in corporations. (reverse coded)
44. Information from corporations is trustworthy.
45. I trust corporations to do what is right.
46. Corporations have too much power and influence in society. (reverse coded)
47. Corporations look out for my interests.
48. Corporations often do not tell the public the truth. (reverse coded)
49. I am suspicious of corporations. (reverse coded)

Results

With marital state (reference group: unmarried), employment (reference group: full-time employed), and cities of residence (reference group: non-municipalities) being dummy-coded, we entered the variables into multiple regression models with SPSS 21 to yield the outcomes presented below.

H1: Government trust is positively associated with a) AI trust and b) AI science community trust.

With government trust set as the independent variable and AI trust and AI science community trust set as the dependent variable(s), we find that government trust directly relates to AI trust (β = .29, p < .001) and AI science community trust (β = .19, p < .001). Hence, H1a and H1b are supported (Table 1).

H2: Corporation trust is positively associated with a) AI trust and b) AI science community trust.

With corporation trust set as the independent variable and AI trust and AI science community trust set as the dependent variable(s), the findings show that corporation trust has a positive bearing on AI trust (β = .15, p < .001) and AI science community trust (β = .18, p < .001). Thus, H2a and H2b are supported (Table 1).

Table 1. Multiple regression of news attention, institutional trust, and science trust.

	AI trust	AI science community trust
	Beta	Beta
Government trust	.29***	.19***
Corporation trust	.15***	.18***
General news (via new media)	.07	−.07
General news (via old media)	−.08*	−.04
Political news	−.06	−.01
Scientific news	.08*	.01
Adj R^2	.14	.09

*p < .05, **p < .01, ***p < .001.

Table 2. Multiple regression of news attention and institutional trust.

	Government trust	Corporation trust
	Beta	Beta
General news (new media)	−.05	.09*
General news (old media)	−.05	.08*
Political news	.11*	−.18***
Scientific news	.04	.06
Adj R^2	.01	.01

*p < .05, **p < .01, ***p < .001.

RQ1: Does attention to general news affect government trust, corporation trust, AI trust, and AI science community trust?

Our findings reveal that attention to general news via both kinds of media is irrelevant to government trust, but directly relates to corporation trust (via Internet: $\beta = .09$, $p < .05$; via old media: $\beta = .08$, $p < .05$), as Table 2 suggests. Furthermore, attention to general news via Internet media is irrelevant to AI trust and AI science community trust (Table 1). Finally, attention to general news via conventional media is inversely associated with AI trust ($\beta = -08$, $p < .05$), as Table 1 presents.

RQ2: Does attention to political news affect government trust, corporation trust, AI trust, and AI science community trust?

Attention to political news is positively associated with government trust ($\beta = .11$, $p < .05$), but inversely with corporation trust ($\beta = -18$, $p < .001$) (Table 2). On the other hand, it has no significant bearing on either AI trust or AI science community trust (Table 1).

RQ3: Does attention to scientific news affect government trust, corporation trust, AI trust, and AI science community trust?

Attention to scientific news is insufficiently associated with either government trust or corporation trust (Table 2). Furthermore, it is positively associated with AI trust ($\beta = .08$, $p < .05$), but not with AI science community trust (Table 1).

The outcomes of our demographic regression analysis suggest that the demographic variables including age, education, gender, marital status, employment, city of residence, and monthly family income, as a whole, are more indicative of news consumption than trust in government, corporations, and AI science (Tables 3 and Tables 4). As Table 3 shows, among all the demographic variables, only job status (full-time students) positively predicts public trust in AI science community ($\beta = .13$, $p < .001$), and no variable is significantly related to AI trust. In addition, men have more faith in corporations than women ($\beta = .10$, $p < .001$), and full-time students are more inclined to trust corporations than people out of

Table 3. Multiple regression of demographics, institutional trust, and science trust.

	Government trust	Corporation trust	AI trust	AI science community trust
	Beta	Beta	Beta	Beta
Age	−.14***	.04	−.05	.06
Education	.09*	−.04	.03	−.05
Sex: males	.02	.10***	−.04	−.06
Marital state: married	−.02	−.04	−.03	.05
Employment: part-time	−.07*	.03	−.01	.03
Employment: students	−.03	.10*	.03	.13***
Employment: unemployed	−.03	.01	.00	.03
Employment: others	.04	−.04	−.03	−.03
Residence: municipalities	.02	−.01	−.02	−.04
Monthly family income	.05	−.02	.05	.00
Adj R^2	.01	.02	.00	.01

*$p < .05$, **$p < .01$, ***$p < .001$.

Table 4. Multiple regression of demographics and news attention.

	General news via new media	General news via old media	Political news	Scientific news
	Beta	Beta	Beta	Beta
Age	−.08	.14***	.01	−.01
Education	.14***	.05	.16***	.16***
Sex: males	−.03	.06	.11***	.23***
Marital state: married	.10*	.06	.05	.11***
Employment: part-time	−.06	.00	.01	−.05
Employment: students	.00	−.01	.08	.00
Employment: unemployed	−.05	−.06	−.05	−.02
Employment: others	−.05	−.07*	−.05	−.02
Residence: municipalities	.07*	−.03	.04	.03
Monthly family income	−.03	−.06	.02	.04
Adj R^2	.02	.04	.03	.10

*p < .05, **p < .01, ***p < .001.

jobs as well as those employed full-time and part-time (β = .13, p < .05). Finally, as to government trust, education is the only independent variable directly associated with government trust (β = .09, p < .05) whereas age (β = −.14, p < .001) and part-time employment (β = −.07, p < .05) are inversely associated with it. On the other hand, when it comes to consumption of preferred news (Table 4), education is the most effective indicator and positively related to general news via new media (β = .14, p < .001), political news (β = .16, p < .001), and scientific news (β = .16, p < .001). Gender is the second most predictive variable, directly associated with political (β = .11, p < .001) and scientific news (β = .23, p < .001). Lastly, age positively predicts consuming general news via old media (β = .14, p < .001).

Discussions

This study approaches AI as a communicative partner with which people create meaning and convey information to each other in human society. To achieve that, we have to situate the research of public trust in AI in people's world views so that we are able to see how the role of this unprecedented communicative partner in the society is perceived by people in relation to their belief in the two foremost institutions formulating human society: government and corporations. Our results support the existing studies arguing via the theory of motivated reasoning that public attitudes toward government and corporations directly affect people's science trust in AI.

Although existing research tends to treat science trust as a homogenous and single construct, our study more vitally advances the literature by proposing evidence that individuals develop disparate attitudes toward AI and the AI science community and that their trust in the technology as well as those who are developing AI varies. This discovery suggests that researchers should contemplate the likelihood that the masses' acceptance of AI in everyday life is also shaped by public perceptions of science community such as its honesty, integrity, and transparency, and that it is possible the masses have no trouble trusting AI, but instead refrain from using AI due to skepticism toward AI science community. Although we do not find strong evidence, our results do show that the participants have higher trust in AI (mean = 3.38) than its science community (mean = 2.40).

In addition to confirming that participants' trust in both AI and its science community is encouraged by their attitudes toward government and corporations, the second part of our study explores how people's world views on government, corporations, AI, and AI science community are influenced by news they prefer to consume. Our findings indicate that news consumption plays a consequential role depending on news types. First, it comes as little surprise that scientific news consumers are most likely to trust AI (but not the AI science community). Despite contributing little to trust in government and corporations, consumption of scientific news effectively augments AI trust, which is simultaneously reinforced by government and corporation trust. Second, albeit having no substantial influence on either AI or AI science community trust, political news consumption indirectly encourages science trust by increasing government trust, which positively relates to science trust. Lastly, general news consumption enfeebles AI trust while at the same time enhancing corporation trust that directly is associated with AI trust.

Not one news type overall directly influences the AI science community trust, and there are a few probable reasons for this trend. One of them is scientists' long-lasting passiveness for communicating professional topics with laypeople; hence, technologies usually get more attention and exposure than scientists (Scheufele, 2014; Sharon & Baram-Tsabari, 2014). The other reason is that there are still many inscrutable puzzles beyond humans in the field of AI such as block box problems and ethical issues (Castelvecchi, 2016), and scientists are reluctant to address them until there is a concrete policy in place (Deng, 2015; Gulson & Webb, 2017; Neri & Cozman, 2019). Moreover, although there are several studies inspecting people's science trust in relation to news consumption, our research furthers the analysis by discussing news consumption and its influence as an integral part of participants' world views. By doing so, we are able to see not only the direct influence of each news type on science trust, but also the indirect influence exerted by news types through shaping people's perceptions of government and corporations on science trust. Political news consumption in particular exemplifies the indirect influence of news via people's world views as mediators.

The third and final part of the study investigates how the participants' demographic backgrounds affect their news consumption, attitudes toward government and corporations, as well as trust in AI and its science community. There has been a large strand of research focusing on these factors. The experiment of Tussyadiah and Miller (2019) reveals that age is one of the most prominent predictors; people over 55 years old are significantly more resistant of AI services than other age groups. The reports of Carter (2018) and Broussard et al. (2019) point out that employment is highly indicative of fear of existential crises arising from AI; people in a senior position at work are more anxious over being replaced by robots and massive automation. The survey of Gherheș and Obrad (2018) demonstrates that attitudes toward AI mainly depend on education; owners of a bachelor's or graduate degree show an affinity for integrating AI into workflow than those without such a degree (Khakurel et al., 2018). We obtain indirect evidence upholding the aforementioned conclusions.

Beyond our anticipations, demographic variables mostly affect science trust via news consumption and institutional trust as mediators rather than directly. For example, age mitigates government trust, which encourages AI and science community trust. Education and gender cause a robust influence on the consumption of political, scientific, and online general news, which further effects the participants' institutional trust and science trust. Based on our findings, we can conclude that people's demographic backgrounds rarely exert direct impacts on their attitudes toward AI. Instead, demographic factors determine information that they tend to absorb and shape their understandings of politics and corporates, which decide how they perceive AI and its science community.

To sum up, as AI is getting more and more quasi-human properties, people's interaction with it is moving beyond traditional communication theories. We need to start treating communicative AI as a partner with which people communicate rather than a medium via which people exchange information with each other. To look into how the course where AI is developing its social role in human society responds to people's perceptions of AI, we suggest to examine science trust in AI as well as its science community in association with attitudes toward social institutions and news reading behavior. As an explorative study, our findings have opened the door for researchers to investigate human-machine interaction through the lens of mankind's world views. We recommend that future research can deal with this topic from a specific social aspect such as public support of AI regulation policy and AI emerging role in the patient–provider relationship (Wilner, 2018).

This study has a number of limitations. One of the most noticeable weaknesses is that the participants' feedbacks were likely based on their experience of using divergent AI services. AI is used for a vast variety of services (e.g., virtual assistants, reverse image searching, news bots), and they are associated with certain types of crises. For example, massive employment of robots as the main workforce would damage the sustainability of the human society; virtual assistants adopted to administer public services might encourage further marginalization of the minority groups. Consequently, approaching AI as a homogenous subject in this survey limited the diversity of the feedbacks. In addition, some previous studies reveal that the masses tended to overestimate their own understandings of controversial technologies (Cui & Wu, 2019; Jho et al., 2014). As our survey did not either prepare AI knowledge items to verify the participants' understandings of AI or investigate their recent experience of using AI services, we did not know if their feedbacks were based on adequate knowledge of AI and valid user experience. Last but not least, according to existing research (Gauchat, 2012; Pechar et al., 2018), germane to public attitudes toward government, support of political parties could be a critical predictor of public opinion on controversial novel technologies. While our survey did not look into the participants' political party preferences, future research is recommended to take partisanship into account.

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