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**Awareness of artificial
intelligence:
Diffusion of
information about AI
versus ChatGPT in the
United States**



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ABSTRACT

AWARENESS OF ARTIFICIAL INTELLIGENCE: DIFFUSION OF INFORMATION ABOUT AI VERSUS CHATGPT IN THE UNITED STATES

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This paper addresses the awareness about the artificial intelligence across states in the United States. We uniquely create indices of Google internet search results for general AI awareness and about ChatGPT, normalizing alternatively by internet users and land area. An understanding of the awareness about AI would provide useful insights into regulatory attempts to monitor and guard the AI technologies, besides suggesting alternatives for laggard states to catch up. Econometric results to explain the drivers of AI awareness show that, ceteris paribus, more prosperous states had greater awareness about AI and ChatGPT. On the other hand, states with greater economic freedom had a lower awareness. States with more men to women has lower AI awareness when hits were normalized by area, but the reverse was true when weighted by internet users. States with a higher proportion of the elderly population were no different from the other states, while those with greater urbanization had more AI/ChatGPT awareness when the internet hits were weighted by land area. Finally, states bordering Canada were no different from other states, while states bordering Mexico generally had a lower AI/ChatGPT awareness.

Keywords: artificial intelligence; AI; ChatGPT; Internet; machine learning; Google search; economic freedom; urbanization; gender

JEL classification: O33; D83; L86

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1. Introduction

The advent of artificial intelligence (AI) in recent times and the more recent invention of bots like ChatGPT have become (and are increasingly becoming in other instances) nothing short of game changers. The ability of AI and machine learning tools to rapidly glean extant information and to remember and learn from processes is continuing to challenge human cognition, besides opening new frontiers of possible products and processes. In one sense, AI technologies impact both the quantity and quality of inputs into existing production methods, while also having the ability to create new products and processes. Changes in both the quantity (e.g., labor saving) and quality (e.g., better accuracy) makes it hard to weigh the equity-efficiency tradeoff from the adoption of new AI systems. And the challenge is compounded when new products/processes are generated by AI, since there is then an absence of a benchmark for comparison (“how much labor is an AI technology replacing?”).

Furthermore, when AI is able to develop new technological trajectories (e.g., different chemical combinations for medical drugs, more delicate medical surgeries, etc.), the technology charts a new territory, and, over time, that might generate even different technologies. Thus, monitoring and effective resource allocation would become problematic.

A relatively familiar example is with respect to the self-driving cars. The liability in case of accidents is not completely clear and this is challenging insurance companies, regulators, and firms that do business in running driverless taxis. Again, as the scope of AI expands, these issues are going to be compounded, both on the positive and negative aspects of AI.

Agrawal et al. (2017) was one of the first studies to highlight the changes brought about (or about to be brought about) by artificial intelligence. Over time, different authors have considered the various potential applications of AI technologies and their implications for economics and business (see for examples, Agrawal et al. (2019), Dirican (2015), Henriquez (2023), Jia et al. (2023), Nah et al. (2023)). However, not all potential implications of AI are positive, and some, such as privacy concerns, go beyond the more obvious and immediate concerns about potential job losses in some industries (see Nah et al. (2023)).

These adverse implications warrant government monitoring and intervention to address inequities and market failures. Regulators are trying to scramble to regulate/monitor AI technologies, but their wide scope and fast evolution provides somewhat of a unique regulatory challenge (Wheeler (2023)). However, a crucial precursor to any related regulatory intervention is a good understanding of how information about AI is diffusing. Obviously, not all aspects of AI are bad, and it would be relevant to see whether, for example, the digital divide is impacting the public’s ability to learn about and access these technologies. Indeed, a recent study by the Pew Research Center has noted that, “Awareness of common uses of artificial intelligence is a first step toward broader public engagement with debates about the appropriate role – and boundaries – for AI”, (Kennedy et al. (2023)).

This paper adds to our understanding of AI by focusing on what drives awareness about artificial intelligence, making the distinction between awareness of general AI versus ChatGPT – currently, the most popular related brand or application. This consideration can be broadly seen as addressing the diffusion of general technological knowledge versus applied technical knowledge. For this purpose, we construct two unique indices of internet search results for each U.S. state to quantify awareness about AI and ChatGPT. These searches required various refinements to reduce noise in the search results and these are discussed in detail in Section 2.2. In the spectrum of the fast-emerging literature on the economics of AI, only a handful of studies have considered AI awareness (Flavian et al. (2021), Kong et al. (2021)), but none has created a wide-ranging index and considered its drivers as the present study.

Our results show that, *ceteris paribus*, more prosperous states had greater awareness about AI and ChatGPT. On the other hand, states with greater economic freedom had a lower awareness. States with more men to women has lower AI awareness when hits were normalized by area, but the reverse was true when weighted by internet users. States with a higher proportion of the elderly population were no different from the other states, while those with greater urbanization had more AI/ChatGPT awareness when the internet hits were weighted by land area. Finally, states bordering Canada were no different from other states, while states bordering Mexico generally had a lower AI/ChatGPT awareness.

The layout of the rest of the paper includes the background and the model in the next section, followed by data and estimation, results, and conclusions.

2. Background and model

2.1 Background

A majority of the economics/business research on AI has been related to potential job market implications (see Acemoglu et al. (2021), Acemoglu and Restrepo (2020, 2019), Agrawal et al. (2023, 2019)). The labor-saving implications and the potential differences/limits of applications across industries have garnered considerable research attention, although the full implications of AI technologies is yet to be realized. For this primary reason, effective policy recommendations have not yet emerged in this regard.

Furthermore, besides the potential applications AI technologies e.g., in healthcare, logistics, transportation, etc. (Agrawal et al. (2019), Dirican (2015), Henriquez (2023), Jia et al. (2023), Nah et al. (2023)), potential negative aspects, related to privacy, misinformation, bias (economic, digital, gender), etc. have been noted (Nah et al. (2023)), again, with few concrete policy solutions.

In addition to the rapid pace of AI technologies with unknown full scope of potential applications, a crucial missing ingredient in policy formulation is an understanding of what

drives AI awareness (Kennedy et al. (2023)). It is towards this issue that the present research is directed.

Besides focusing on the diffusion of information about basic and applied research, the awareness about ChatGPT (which is a brand name) would have implications for market concentration. Regulators have been considering the potential implications of market concentration, with the United States is lagging Europe in regulating AI (Wheeler (2023)).

Flavian et al. (2022) and Kong et al. (2021) are among the very few studies that formally consider AI awareness. Kong et al. (2021) used survey data from Chinese hospitality industry employees and found a positive relationship between AI awareness and job burnout. However, the authors found no direct relationship between AI awareness and career competencies.

Flavian et al. (2022) considered data on 404 North American robo-advisors in banking and financial management, and examined how customers' technology readiness and service awareness affect their intention to use analytical AI investment services. Their results showed that customers' technological optimism increases, and insecurity decreases, their intention to use robo-advisors. Furthermore, feelings of technological discomfort positively influenced the adoption of robo-advisors.

So, while there is some recognition of the issue of AI awareness, the aspects covered in the present study are unique.

2.2 Measuring the awareness of artificial intelligence among the states

The awareness about artificial intelligence across the states in the United States is captured via a search in Google, with terms and state names. Specifically, two searches were simultaneously conducted:

- Search A string: How to use "AI OR artificial intelligence" "state name"
- Search B string: How to use "ChatGPT OR AI" "state name"

The quotation marks ensure that the terms in quotations show up in every search.¹

The two search strings address qualitatively different aspects of awareness, both of which would have policy relevance. String A is capturing general awareness about AI and such a search would be done by a relative novice getting his or her feet wet to become familiar with the new technology. String B, on the other hand, would be likely done by a relatively more informed internet user who is aware of ChatGPT. It would also capture awareness about the ChatGPT brand, which has been in regulatory focus already (<https://apnews.com/article/chatgpt-openai-ceo-sam-altman-congress-73ff96c6571f38ad5fd68b3072722790>).

¹ Putting the whole string in the same quotation would limit searches to websites that specifically carry the whole string. That would drastically limit the search results and would not adequately capture awareness.

Six states especially needed some refinements to reduce noise in the search results:

- i. North Carolina and North Dakota: searches were done with minus South;
- ii. South Carolina and South Dakota: searches were done with minus North;
- iii. State of Virginia search was done with minus West to delete references to West Virginia;²
- iv. The search for the State of Washington was particularly challenging, with noise from websites hosted in or referring to Washington, DC, Washington University in St. Louis, and the Washington Post newspaper. Therefore, the search for the Washington had (a) minus DC; (b) minus District;³ (c) minus Louis;⁴ and (d) minus Post (to delete references to the Washington Post newspaper).

However, since search research can vary over time, even during a short period of time, the searches were done in a single sitting and in the shortest time possible (without any breaks). Furthermore, the time variation is controlled for redoing the searches at another time period, accounting also for weekday versus weekend spikes (e.g., some websites might be down on the weekend while others may be launched as test sites only for the weekend), as well as time of day (am versus pm).

These refinements ensure that we have a pretty good handle on the prevalence or diffusion of information about artificial intelligence.⁵ Given the internet-based nature of AI, the internet search methodology is especially relevant in this regard to capture related awareness. Still, there may be duplication with mirror sites that we are unable to control for.

This underlying internet search method had been developed by Goel et al. (2011) to study the cross-national awareness about corruption. The language issues and differences in search engines used across nations is less of a concern when one focuses on states in the United States.

For instance, the top 3 search results for California in String A were:

1. California Department of Technology, “The Promise of AI in California Government”, <https://techblog.cdt.ca.gov/2020/11/7162/>

² Conversely in the search for West Virginia, this would be less of a concern since both West and Virginia were in the same quotation marks during the relevant search.

³ Referring to the District of Columbia.

⁴ Referring to St. Louis. Note that the minus correction in Google search only addresses the immediate word after the minus sign, and in this case, Louis seemed more pertinent than St. (since there would be St. prefix to something else housed in the State of Washington).

Note further that the Louis correction was aimed primarily to weed out references to Washington University in St. Louis. However, deleting University would also eliminate universities in the State of Washington (University of Washington, Washington State University, etc.).

⁵ Several resources are available on the web with suggestions about how to refine interest searches and make them more relevant. For example, see <https://www.theguardian.com/technology/2016/jan/15/how-to-use-search-like-a-pro-10-tips-and-tricks-for-google-and-beyond>

2. California Department of Technology, “Artificial Intelligence Community of Practice”, <https://cdt.ca.gov/technology-innovation/aicop/>
3. The Brookings Institution, “California charts the future of AI”, <https://www.brookings.edu/articles/california-charts-the-future-of-ai/>

Correspondingly, the top three searches for California with String B were:

1. Digitaltrends, “ChatGPT: the latest news, controversies, and tips you need to know”, <https://www.digitaltrends.com/computing/how-to-use-openai-chatgpt-text-generation-chatbot/>
2. Whatplugin, “California Law”, <https://www.whatplugin.ai/plugins/california-law>
3. Gptstore, “Overview Of AI/ChatGPT Plugin California Law”, <https://gptstore.ai/plugins/law-plugin-herokuapp-com>

Based on these examples, it is evident that the search results in both cases are relevant, providing useful information to a potential user. Understandably, however, given the commercial nature of ChatGPT, the search results with String B are more of commercial nature. Roughly speaking, String A search results can be viewed as relating more to the diffusion of related basic knowledge, while String B results are more of the diffusion of applied knowledge.

All search results were weighted by state size (land area) and internet users (to address cross-state digital divide). Figures 1-4 show the internet search results, weighted alternately by state land area and internet users. We see considerable variation in the top and bottom states, depending upon the weighting used. Thus, the alternative normalization employed would be a good test of the robustness of our findings.

Table 1 shows that the variability in the internet search results was greater when the search results were weighted by land area, compared to when they were weighted by internet users.

2.3 Model

With individual observations at the U.S. state level in our cross-sectional analysis, the dependent variable(s) is the internet searches (weighted alternatively by the estimated number of internet users in a state and state land area), using the Strings A or B with state name as described above. To explain this, we employ the following model:

$$(\text{Internet hits})_{ijt} = f(\text{INCOME}_{pci}, \text{EconFREE}_i, \text{GENDER}_i, \text{URBAN}_i, \text{ELDERLY}_i, \text{MEXICO}_i, \text{CANADA}_i) \dots(1)$$

$i = 1, 2, \dots, 50$

$j = \text{AI_land}, \text{AI_user}, \text{ChatGPT_land}, \text{ChatGPT_user}$

$t = \text{Tuesday, October 3 pm; Sunday, October 8, am.}$

The alternative dependent variables allow us to see the effects of alternative weightings of internet hits, along with the two dimensions focusing on general AI awareness and a more specific awareness targeted to ChatGPT.

Economic prosperity (INCOMEpc) captures affordability in the demand and production of internet sites for AI. Other things being the same, more prosperous states would also have better institutions, *ceteris paribus*.

Economic freedom (EconFREE) captures lack of government regulations, accounting for the fact that state-level autonomy in the U.S. federalist system gives states considerable leeway in framing their laws. Regulations would impact the propensity to trade in general, also including the AI.

The elderly share of the total population (ELDERLY), male to female gender ratio (GENDER), and relative shares of urban versus rural population (URBAN) account for demographic-geographic differences that are likely to address differences in the digital divide and other aspects that might influence propensities to post on and access the internet. For instance, gender inequalities might be important in women's access to the internet and AI technologies, and the use of AI technologies might empower women in some instances (see UNESCO/OECD/IDB (2022)).⁶

Finally, MEXICO and CANADA are dummy variables that identify states sharing foreign borders. Internet activity (and other economic activity) in these states might be somewhat different from other states (due, for example, to a greater influx of transient foreign population).

3. Data and estimation

3.1 Data

The right-hand-side explanatory variables in equation 1 are drawn from the U.S. government and other reputed sources that are routinely used in the literature. The average urbanization rate among the 50 states in our sample (DC was excluded) was about 72 percent. The mean share of elderly population among the states stood at approximately 17 percent. There was, however, considerable variation across states.

Complete details about the variables used, including variable definitions, summary statistics, and data sources are provided in Table 1. Table 2 reports correlations between the key variables in the analysis. The correlation between AI_user and ChatGPT_user and that between AI_land and ChatGPT_land are high, compared to the other correlations.

⁶ The different weighting of internet searches makes a difference in the gender context, because the genders are variously distributed across U.S. states. In our sample, the correlation between state land area and GENDER is 0.64, while that between internet users and GENDER is 0.1.

3.2 Estimation

We use different estimation techniques in the analysis, depending upon the characteristics of the underlying data and the aspect being addressed.⁷ First, we use OLS regression, with related significance of the estimated coefficients based on robust standard errors. Second, in Table xx, we report results from quantile regression (see Koenker and Hallock (2001) for background on the quantile regression). The quantile regression enables us to examine the relative influence of the control variables across the distribution of the dependent variable(s). How different are the effects of the determinants of AI awareness across states with the least and the most awareness?

4. Results

4.1 Baseline models

Tables 3A and 3B, respectively, show results with the Internet hits using String A and String B, respectively. In each table, we provide results with the dependent variables weighted by land area and internet users, alternatively. Weighting by land area accounts for the state size, while weighting by internet users gets at the digital divide across states.

The results generally show that, *ceteris paribus*, more prosperous states had greater awareness about AI and ChatGPT. This conclusion is statistically strongest when the Internet hits data are normalized by state land area and does not hold when using the String B search when normalized by the estimated number of internet users in a state (Models 1.3A and 1.4A). The positive income – awareness relationship is consistent with greater affordability of and access to internet tools with prosperity, a more educated population, and a brighter potential economic outlook in such states prompting individuals to become more aware and for websites to provide more information about AI.

On the other hand, states with greater economic freedom had a lower awareness. One explanation would be that in more economically free states, there are fewer regulations for alternative business engagement and thus AI services are relatively less in demand.

In terms of relative elasticities, with respect to $INCOME_{pc}$, the elasticity (evaluated at the respective means as reported in Table 1) of AI_{land} was 4.0 (Model 1.1A), while that with respect to $ChatGPT_{land}$ was 4.8 (Model 1.1B). On the other hand, the elasticities with respect to $EconFREE$ were: (i) Model 1.1A: -2.8; (ii) Model 1.3A: -2.9; (iii) Model 1.1B: -3.3; (iv): Model 1.3B: -2.5.

The results with gender ratio showed some interesting differences. States with more men to women had lower AI awareness when hits were normalized by area, but the reverse was true

⁷ In particular, the analysis is cross-sectional, and reverse feedbacks are not a significant consideration (due to the fact that the internet search results lead other variables).

when weighted by internet users. Men might have greater/easier access to jobs in many other professions, although the potential applicability of AI techniques (at least at the relatively nascent AI development stages) might vary across job types.

Interestingly, states with a higher proportion of the elderly population were no different from the other states, while those with greater urbanization had more AI/ChatGPT awareness when the internet hits were weighted by land area (but not when weighted by internet users). The results with elderly make sense when one thinks that the elderly are relatively less likely to be engaged in disseminating information about AI.

States bordering Canada were no different from other states, while the four states bordering Mexico generally had a lower AI/ChatGPT awareness. This shows that, other things being the same, a state's location is somewhat impacting AI awareness.

4.2 Quantile analysis

The quantile regression results are reported in Table 5, using Models 1.1A,B and 1.3A,B, respectively. These results show the relative influence of the control variables across the distribution of the dependent variables, i.e., the awareness about AI versus ChatGPT. The respective "full sample" OLS results from the earlier tables are also reported for ease of comparison.

The results show that the influence of determinants does vary with the prevalence of awareness across states. Generally speaking, the impact is greater, both in magnitude and statistical significance, at the upper end of the distribution. In other words, states with a higher footprint of AI experience more pronounced effects (which could be negative or positive, depending upon the aspect considered). This suggests that there is likely a threshold level of awareness and policy to be effective would have a greater impact in states that are beyond the awareness threshold. Furthermore, the results when weighting the dependent variables by land area are relatively stronger compared to the results when weighting by internet users.

4.3 Robustness checks

4.3.1 Using a different time of internet searches

Since internet search results can change momentarily, the basic searches were redone at another time, accounting for weekend and the time-of-day variations (see Section 2.2 for details).

Table 4 shows that the search means across the two time periods were comparable. Further, the correlation between two time periods when the internet searches were conducted exceeded 0.9 for each of the four measures of Internet awareness that we considered in this analysis.

The results using the latter time period were quite similar to what is reported in Tables 3A and 3B. Complete details are available upon request from the authors. This robustness confirms the validity of our main findings in the face of possible changes in search results over time.

4.3.2 Considering additional controls

To examine other influences on AI awareness, we considered the influence of language (non-English speakers (NoEnglish)), education (EDU), and unemployment (UN), in alternative variations of the baseline models. Broadly speaking, these may be tied to accounting for the digital or information divide.

The results (not reported here but available upon request) showed that the respective coefficients were statistically insignificant in all cases, the lone exception being the positive and statistically significant sign for NoEnglish when AI_user is used as the dependent variable. Non-English speakers might have a greater incentive to be aware of when the AI offered and there may be more websites targeting them. The insignificance of the coefficients on UN and EDU may be attributed to the fact that the per-capita income variable would capture some of these aspects.

4.3.3 Checking for nonlinear effects

Whereas the quantile regression above accounted for some aspects of nonlinearity, we also examined nonlinearities in the independent variables by alternately including the squared terms of INCOMEpc and EconFREE in the baseline models.

The results failed to show any linear effects with respect to INCOMEpc. However, the effect of economic freedom (EconFREE) exhibited a U-shaped relation, with the coefficient on the squared term being positive and significant. This was true whether the internet hits were weighted by internet users or state land area. The findings for the other controls were in general agreement with what is reported in the baseline models. Again, full details are available upon request. The concluding section follows.

5. Concluding remarks

The explosion of artificial intelligence in recent times has policymakers scrambling to keep pace with the rapid technological change and consider whether new regulations and policies would be needed (Wheeler (2023)). However, a crucial precursor to any government intervention, in fact to the use of AI technologies, is a good understanding of what drives awareness about these new processes (Kennedy et al. (2023)). It is in this regard that the present research aims to make a contribution. A better understanding of the drivers of awareness would also better inform government support for these new technologies (see Chowdhury et al. (2022a, b)).

This paper addresses the awareness about the artificial intelligence across states in the United States. We uniquely create indices of Google internet search results for general AI awareness and about ChatGPT, normalizing alternatively by internet users and land area (see Figures 1-4). An understanding of the awareness about AI would provide useful insights into regulatory

attempts to monitor and guard the AI technologies, besides suggesting alternatives for laggard states to catch up.

Results to show the state-level determinants of AI awareness reveal that, *ceteris paribus*, more prosperous states had greater awareness about AI and ChatGPT. On the other hand, states with greater economic freedom had a lower awareness. A one percent income state personal income per capita would increase general internet awareness by about four percent (AI_land in Model 1.1A), while a similar increase in per capita income would increase ChatGPT awareness by about five percent (ChatGPT_land in Model 1.1B). The quantile regression results (Table 5) underscore the point that there might be some threshold level of AI awareness that policymakers especially in the laggard states might want to keep in mind.

States with more men to women has lower AI awareness when hits were normalized by area, but the reverse was true when weighted by internet users. These different findings might be due to the different distribution of males versus females across states (and these distributions would likely be different from the gender distribution of internet users), and the different prevalence of industries where women are relatively better represented compared to their male counterparts (e.g., school teachers, nursing, etc.).

Our results also suggest that, given the negative coefficients on the index of state economic freedom, policymakers dismantling regulations and promoting economic freedom should be cognizant of the spillovers on AI awareness.

With respect to demographic-geographic influences, states with a higher proportion of the elderly population were no different from the other states, while those with greater urbanization had more AI/ChatGPT awareness when the internet hits were weighted by land area. It could be the case that, given the nascent and rapid pace of AI technologies, the supply and demand for these technologies is not currently targeted to the elderly.

Finally, states bordering Canada were no different from other states, while states bordering Mexico generally had a lower AI/ChatGPT awareness. The negative results for the Mexico-border states might be attributed to a relatively greater proportion of non-native English speakers.

Overall, this research has provided formal insights into the awareness of AI versus ChatGPT across the U.S. As the AI applications evolve, including applications to glean awareness information from the internet, future studies could expand on related aspects.

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Table 1
Variable definitions, summary statistics, and data sources

Variable	Mean (std. dev.)	Min./Max.	Source
Number of Google hits by state for the query <i>how to use "AI OR artificial intelligence"</i> per square mile state land area, October 3, 2023. [<i>AI_land</i>]	537.2 (773.4)	4.1 3,336.1	[1]
Number of Google hits by state for the query <i>how to use "AI OR artificial intelligence"</i> per estimated internet users in a state, October 3, 2023. [<i>AI_user</i>]	4.4 (4.2)	0.2 23.2	[1]
Number of Google hits by state for the query <i>how to use "ChatGPT OR AI"</i> per square mile state land area, October 3, 2023. [<i>ChatGPT_land</i>]	2,804.4 (4,595.0)	77.9 19,223.3	[1]
Number of Google hits by state for the query <i>how to use "ChatGPT OR AI"</i> per estimated internet users in a state, October 3, 2023. [<i>ChatGPT_user</i>]	20.1 (16.4)	3.3 85.8	[1]
Per Capita personal income (in thousands), 2022. [<i>INCOMEpc</i>]	63.2 (8.6)	46.4 84.6	[2]
Economic Freedom (scores range from 0 to 10 where larger numbers imply greater freedom), 2020. [<i>EconFREE</i>]	6.2 (1.0)	4.3 7.9	[3]
Gender ratio – ratio of men to women (100 = parity), 2021. [<i>GENDER</i>]	97.8 (3.2)	93.6 109.2	[4]
Urban population (%), 2020. [<i>URBAN</i>]	72.4 (14.8)	35.1 94.2	[5]
Percentage of the population 65 years of age and older, 2020. [<i>ELDERLY</i>]	17.4 (2.0)	11.7 21.8	[6]
State has border with Mexico (1 = yes, 0 = no). [<i>MEXICO</i>]	0.08 (0.3)	0.0 1.0	
State has border with Canada (1 = yes, 0 = no). [<i>CANADA</i>]	0.26 (0.4)	0.0 1.0	

Notes: $N = 50$.

Sources:

[1]. Google hits: Author's calculation – see text for details. Land area: Total area measured in square miles as of January 2010. <https://www.census.gov/geographies/reference-files/2010/geo/state-local-geo-guides-2010.html> (accessed October 2023). Internet users: Internet penetration in a state as of November 2021, retrieved October 2, 2023, from <https://statista-com.ezproxiz.uakron.edu:2443/statistics/184691/internet-usage-in-the-us-by-state/>.

Population: 2022 population estimate - www.bea.gov. (accessed October 2023)

[2]. U.S. Bureau of Economic Analysis. www.bea.gov. (accessed October 2023)

[3]. Fraser Institute. <https://www.fraserinstitute.org/economic-freedom/dataset?geozone=na&year=2020&selectedCountry=USA&page=dataset&min-year=2&max-year=0&filter=0>. (accessed October 2023)

[4]. U.S. Census 2021 ACS 5-Year Survey (Table S01010), drawn from

<https://worldpopulationreview.com/state-rankings/sex-ratio-by-state>. (accessed October 2023)

[5]. [https://www.visualcapitalist.com/sp/mapping-us-urbanization-by-state/#:~:text=Not%20surprisingly%2C%20the%20three%20most,%2C%20and%20Vermont%20\(35.1%25\)](https://www.visualcapitalist.com/sp/mapping-us-urbanization-by-state/#:~:text=Not%20surprisingly%2C%20the%20three%20most,%2C%20and%20Vermont%20(35.1%25)). (accessed October 2023)

[6]. U.S. Census, drawn from <https://www.prb.org/resources/which-us-states-are-the-oldest/>. (accessed October 2023)

Table 2
Correlation matrix of key variables

	<i>AI_land</i>	<i>AI_user</i>	<i>ChatGPT_land</i>	<i>ChatGPT_user</i>
<i>AI_land</i>	1.00			
<i>AI_user</i>	0.34	1.00		
<i>ChatGPT_land</i>	0.91	0.16	1.00	
<i>ChatGPT_user</i>	0.37	0.83	0.33	1.00

Notes: See Table 1 for variable definitions. N=50.

Table 3A
Diffusion of information about AI: Baseline models
Dependent variable: Artificial Intelligence

Model →	1.1A	1.2A	1.3A	1.4A
Dep. variable →	<i>AI_land</i>	<i>AI_land</i>	<i>AI_user</i>	<i>AI_user</i>
Per capita personal income [<i>INCOMEpc</i>]	33.96** (2.9)	31.01** (2.8)	0.01 (0.1)	-0.01 (0.2)
Economic freedom [<i>EconFREE</i>]	-244.8** (2.6)	-263.7** (2.8)	-2.05** (2.8)	-2.18** (2.9)
Gender ratio [<i>GENDER</i>]	-104.2** (3.1)	-98.8** (2.7)	0.54* (1.8)	0.57* (1.8)
Urban population [<i>URBAN</i>]	12.62* (1.9)	15.25** (2.3)	-0.01 (0.1)	0.02 (0.3)
Elderly population [<i>ELDERLY</i>]	15.90 (0.3)	12.45 (0.3)	-0.11 (0.2)	-0.14 (0.3)
Border with Mexico [<i>MEXICO</i>]		-412.3* (1.9)		-2.99** (2.1)
Border with Canada [<i>CANADA</i>]		-7.15 (0.0)		0.04 (0.0)
Observations	50	50	50	50
F-statistic	6.82**	5.16**	1.72	1.38
R-squared	0.56	0.58	0.35	0.38

Notes: Variable definitions are provided in Table 1. All models are estimated via ordinary least squares and include a constant term (not reported).

*The numbers in parentheses are (absolute value) z-statistics based on robust standard errors, with ** and *, respectively, denoting statistical significance at the 10% and 5% (or better) levels.*

Table 3B
Diffusion of information about ChatGPT: Baseline models
Dependent variable: ChatGPT

Model →	1.1B	1.2B	1.3B	1.4B
Dep. Variable →	<i>ChatGPT_land</i>	<i>ChatGPT_land</i>	<i>ChatGPT_user</i>	<i>ChatGPT_user</i>
Per capita personal income [<i>INCOMEpc</i>]	212.2** (4.2)	194.8** (3.9)	0.41* (1.8)	0.36* (1.7)
Economic freedom [<i>EconFREE</i>]	-1,509.1** (2.9)	-1,638.4** (3.1)	-7.96** (3.1)	-8.16** (3.2)
Gender ratio [<i>GENDER</i>]	-655.1** (4.9)	-617.0** (4.6)	2.03** (2.1)	2.08** (2.0)
Urban population [<i>URBAN</i>]	68.74* (1.9)	84.55** (2.1)	-0.17 (1.3)	-0.14 (0.9)
Elderly population [<i>ELDERLY</i>]	85.17 (0.4)	64.45 (0.3)	0.47 (0.4)	0.42 (0.3)
Border with Mexico [<i>MEXICO</i>]		-2,657.0* (1.7)		-5.11 (1.0)
Border with Canada [<i>CANADA</i>]		-150.52 (0.1)		0.32 (0.1)
Observations	50	50	50	50
F-statistic	9.64**	7.63**	4.05**	2.86**
R-squared	0.59	0.61	0.42	0.43
<i>Notes: See Table 3A.</i>				

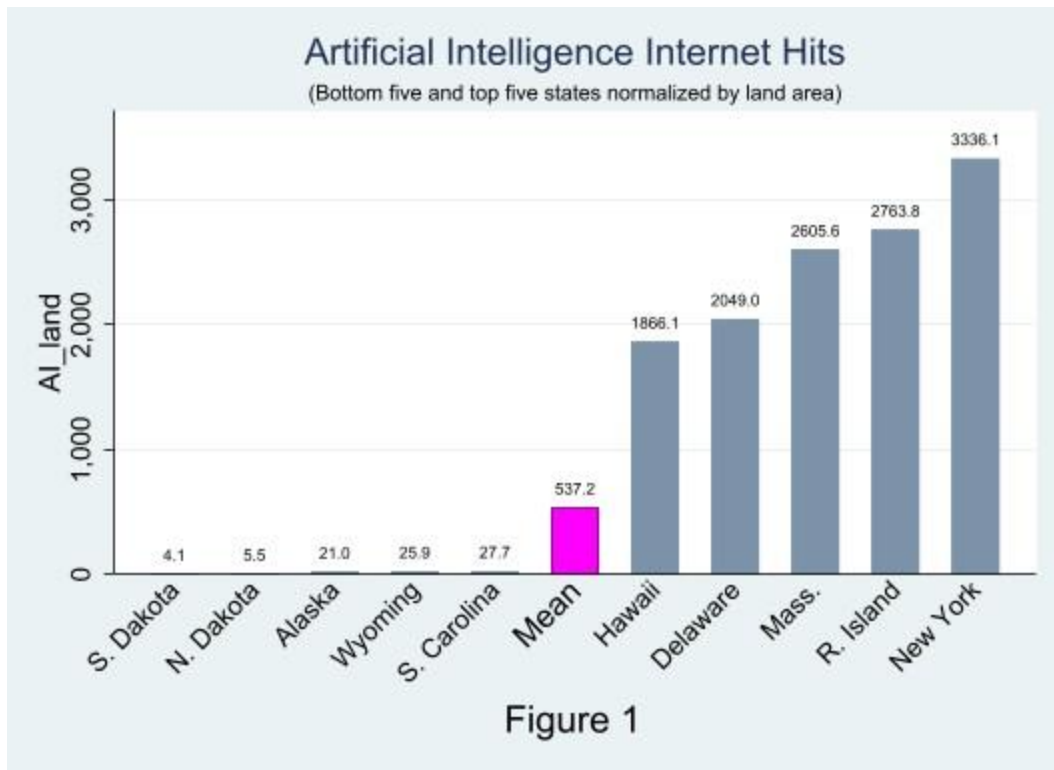
Table 4				
Comparison of normalized internet search results: October 3 versus October 8, 2023				
(mean value of sample)				
Awareness measure →	AI_land	AI_user	ChatGPT_land	ChatGPT_user
October 3, 2023	537.2	4.4	2,804.3	20.1
October 8, 2023	504.2	4.2	2,958.5	21.6
Correlation of measure between the two dates	0.94	0.96	0.96	0.91

Table 5
Relative diffusion of information about AI versus ChatGPT: Quantile analysis

Panel A: Dependent variable – AI_land				
	Full Sample	Quantiles		
	OLS	q25	q50	q75
Per capita personal income [<i>INCOMEpc</i>]	33.96** (2.9)	17.10* (1.7)	38.46** (3.4)	49.40** (2.7)
Economic freedom [<i>EconFREE</i>]	-244.8** (2.6)	-32.74 (0.5)	-123.9 (1.6)	-317.6** (2.1)
Gender ratio [<i>GENDER</i>]	-104.2** (3.1)	-54.47** (2.6)	-80.32** (3.2)	-98.89* (2.3)
Urban population [<i>URBAN</i>]	12.62* (1.9)	2.29 (0.6)	-0.06 (0.0)	18.75 (1.5)
Elderly population [<i>ELDERLY</i>]	15.90 (0.3)	-3.51 (0.1)	-30.90 (0.7)	35.65 (0.5)
Observations	50	50		
R-sq./Pseudo R-sq.	0.56	0.19	0.28	0.41
Panel B: Dependent variable – AI_user				
Per capita personal income [<i>INCOMEpc</i>]	0.01 (0.1)	-0.04 (0.5)	0.06 (0.8)	0.06 (0.6)
Economic freedom [<i>EconFREE</i>]	-2.05** (2.8)	-0.34 (0.5)	-1.22* (1.7)	-1.58 (1.7)
Gender ratio [<i>GENDER</i>]	0.54* (1.8)	0.03 (0.1)	0.34 (1.3)	0.47 (1.2)
Urban population [<i>URBAN</i>]	-0.01 (0.1)	0.01 (0.2)	-0.05 (1.0)	-0.00 (0.0)
Elderly population [<i>ELDERLY</i>]	-0.11 (0.2)	-0.02 (0.1)	-0.06 (0.2)	0.41 (0.6)
Observations	50	50		
R-sq./Pseudo R-sq.	0.35	0.03	0.14	0.20

Table 5 – Cont'd
Relative diffusion of information about AI versus ChatGPT: Quantile analysis

Panel C: Dependent variable – ChatGPT_land				
	Full Sample	Quantiles		
	OLS	q25	q50	q75
Per capita personal income [<i>INCOMEpc</i>]	212.2** (4.2)	100.2* (1.8)	233.4** (3.2)	233.2** (2.1)
Economic freedom [<i>EconFREE</i>]	-1,509.1** (2.9)	-273.7 (0.8)	-714.0 (1.4)	-1,159.1 (1.5)
Gender ratio [<i>GENDER</i>]	-655.1** (4.9)	-275.5* (1.9)	-489.0** (2.8)	-429.7* (1.9)
Urban population [<i>URBAN</i>]	68.74* (1.9)	10.77 (0.6)	21.45 (0.8)	59.00 (0.8)
Elderly population [<i>ELDERLY</i>]	85.17 (0.4)	104.0 (0.6)	-221.4 (1.0)	102.4 (0.3)
Observations	50	50		
R-sq./Pseudo R-sq.	0.59	0.15	0.24	0.43
Panel D: Dependent variable – ChatGPT_user				
Per capita personal income [<i>INCOMEpc</i>]	0.41* (1.8)	0.26 (0.9)	0.28 (1.1)	0.47 (1.0)
Economic freedom [<i>EconFREE</i>]	-7.96** (3.1)	-3.50** (2.2)	-3.59 (1.4)	-7.54* (1.9)
Gender ratio [<i>GENDER</i>]	2.03** (2.1)	0.48 (0.7)	1.10 (1.1)	3.10** (2.3)
Urban population [<i>URBAN</i>]	-0.17 (1.3)	-0.10 (0.6)	-0.13 (0.6)	-0.18 (0.7)
Elderly population [<i>ELDERLY</i>]	0.47 (0.4)	-0.60 (0.6)	1.05 (0.7)	1.46 (0.8)
Observations	50	50		
R-sq./Pseudo R-sq.	0.42	0.14	0.20	0.31
Notes: Variable definitions are provided in Table 1. All models included a constant term (not reported). q50 represents the median regression. Reference model (full sample) reflects results estimated via Ordinary Least Squares with absolute t-statistics based on robust country-level clustered standard errors in parentheses. Absolute value of t-statistics is in parentheses based on bootstrapped standard errors (200 replications) in the quantile regressions.				
* denotes statistical significance at the 10% level, and ** denotes significance at the 5% level (or better).				



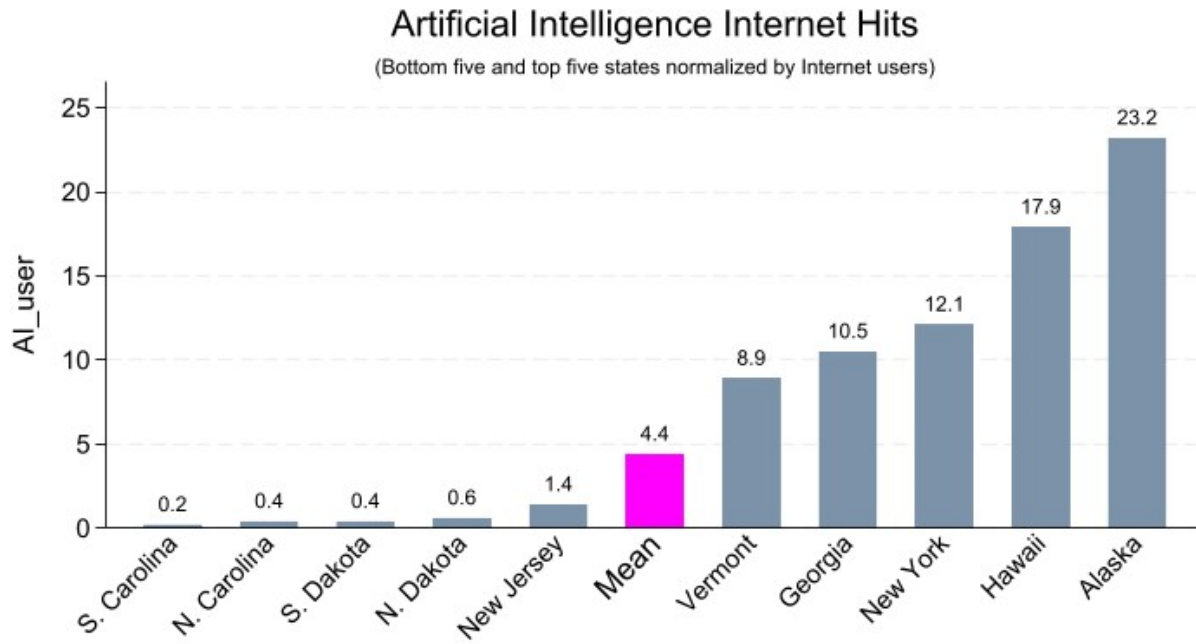


Figure 2

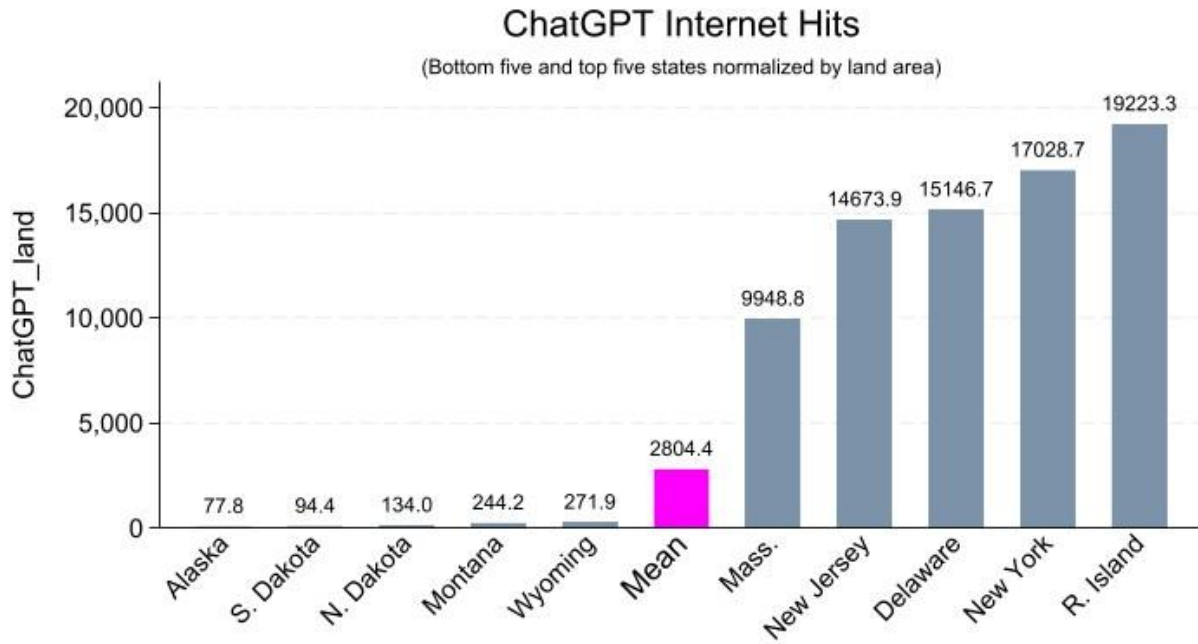


Figure 3

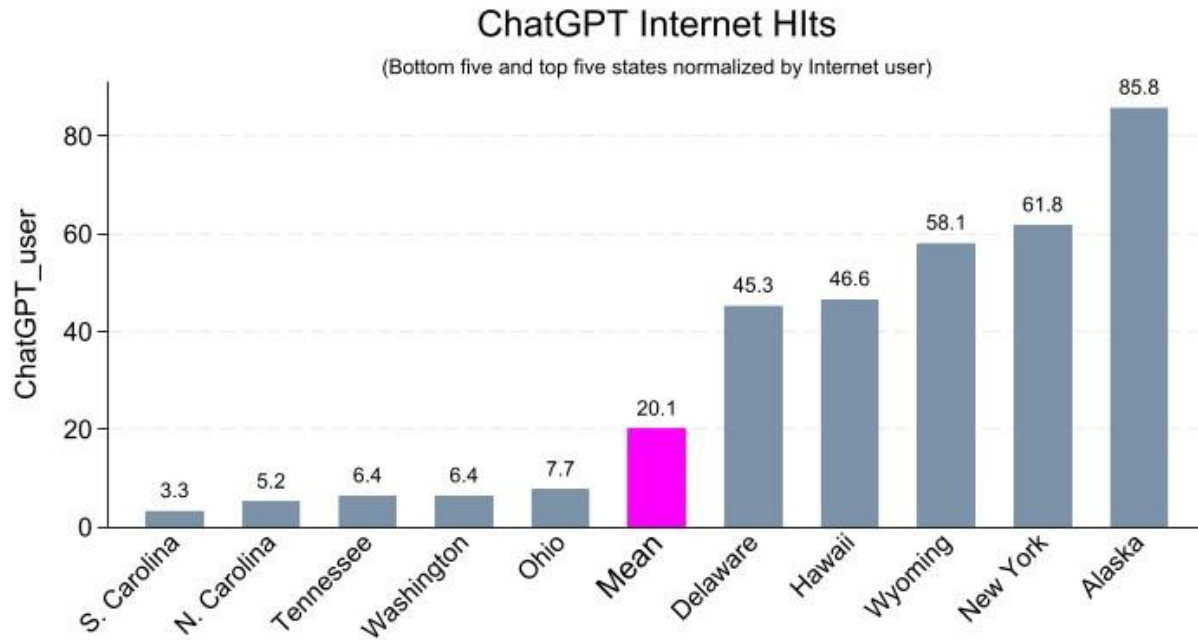


Figure 4