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HEARTLAND HAS LESS TO FEAR FROM AI: EVALUATING OCCUPATIONAL, INDUSTRY AND GEOGRAPHIC EXPOSURE

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The heartland has less to fear in terms of losing jobs to the adoption of artificial intelligence (AI) than other parts of the country — especially some large metro areas along the East and West coasts.

Five heartland states — Arkansas, Mississippi, Indiana, Kentucky and Louisiana — are among the least likely to suffer employment losses; Minnesota is the heartland's only entry among the 10 states rated most likely to feel that pain.

AI tools such as ChatGPT and other large language models (LLMs) will hit hardest in areas where white-collar jobs are concentrated. That list includes the Northeast Atlantic corridor consisting of Boston, New York City, Philadelphia and Washington, D.C., as well as the San Francisco Bay area.

Past waves of automation and "liberalization" of trade policy — think China entering the World Trade Organization in 2001 — devastated heartland communities because of the high concentration of manufacturing operations.

The introduction of ChatGPT has generated heightened interest in the many ways artificial intelligence figures to transform the economic landscape. A study by Goldman Sachs suggests that widespread AI adoption could deliver a 7% boost to the global gross domestic product (GDP) and raise productivity by 1.5 percentage points over a 10-year period.[1] AI will complement some types of labor while being a substitute (destroyer) for others by automating existing human jobs.

The same Goldman study projects that AI adoption could cost the worldwide economy 300 million fulltime jobs. The substitution effect (using AI tools rather than human skills) will most likely appear faster than the new occupations will be created over the long run. A systematic framework is needed to evaluate the likely occupational, industry and geographic dislocations from AI applications.

A key challenge in addressing potential job losses stemming from AI is its burgeoning nature. A dearth exists in the collection of evidence and creation of appropriate tools for an assessment. However, recent research at Princeton University (Felton) and the Stern School of Business at New York University (Raj and Seamans)[2] provides an intriguing systematic approach from AI occupational exposure (AIOE) to industry exposure (AIIE) and, ultimately, geographic exposure (AIGE).

These efforts seemingly have produced the soundest methodology developed thus far, although it has not found its way beyond academic, peer-reviewed journals into the news media and business communities. This article provides — as a framework for evaluation — a synopsis of the aforementioned research with minimized math for a wider, nonacademic audience. We also present a summary of AI exposure in the heartland states relative to other parts of the country.

Occupational Exposure

The first step in measuring job-loss impact is to compare the human abilities, or skills, required in specific occupations to AI applications that can perform those tasks with equal or greater efficiency. Labor is viewed as a bundle of functional characteristics in this approach, where AI algorithms can mimic (learn) from existing data. This is sometimes called "machine learning."

The U.S. Department of Labor maintains the Standard Occupational System (SOC), which describes and categorizes various forms of labor. It includes 10 major sections that are further broken down into subgroups and specific occupations. Linked to this is the Occupational Information Network (O*NET) containing detailed descriptions of occupational requirements. The most current definitions and data on professions nationwide are contained in O*NET.

The AI Progress Measurement project[3] by the Electronic Frontier Foundation (EFF) has created a consistent, well-developed categorization system for AI apps. EFF scrutinizes advances in these apps by examining review articles and academic research papers and AI-related blog posts and websites. EFF requires and verifies documented proof of findings and includes only that data in its system. A thorough review concluded that 10 of the EFF AI application categories experienced meaningful scientific progress over recent history. They include abstract strategy games; image generation; image recognition; instrumental track recognition; language recognition; reading comprehension; real-time video games; speech recognition; translation; and visual question answering.

A crowd-sourced data set was utilized that was based upon survey responses of "gig workers" from Amazon's Mechanical Turk (mTurk) web services.[4] A measure of application-ability awareness was created for each combination of AI application and the 52 occupational abilities found on O*NET. Ability-level exposure is created by the sum of each of the 10 AI apps matched by each occupation. AI occupational exposure is based upon an ability's prevalence and importance within each occupation; it is determined by multiplying the ability-level AI exposure by the prevalence and importance scores for that ability within each occupation. Abilities essential to excel in an occupation will have high scores for both prevalence and importance.

Based upon this methodological framework, the occupations with the greatest exposure to advances in AI applications are white-collar positions mostly requiring advanced degrees. This is attributable to AI technologies being primarily software based, relying upon iterative learning and perception. AI is particularly compatible with tasks entailing categorization, classification and pattern recognition.

Table 1 provides the most- and least-exposed occupations at the six-digit SOC level from this investigation (Felton, Raj and Seamans). Genetic counselors are ranked as most exposed to AI, as they rely on highly codified knowledge. Financial examiners and actuaries are close behind, followed by purchasing agents and budget analysts. Judges and magistrates are the sixth-most exposed, with judicial law clerks in the top 10, as well. Several other professional financial areas are in the top 20, including accountants and auditors, financial managers, and compensation specialists and credit authorizers. Counselors and arbitrators also rank high among those exposed to AI. Occupations least exposed to AI generally require a high degree of physical ability. Examples include dancers, fitness trainers, athletes, painters, masons, roofers, structural iron and steel workers, and bartender helpers.

Table 1: AI Occupation Exposure (AIOE)

RANK	OCCUPATIONS WITH THE HIGHEST AIOE MEASURES	OCCUPATIONS WITH THE LOWEST AIOE MEASURES
1	Genetic counselors	Dancers
2	Financial examiners	Fitness trainers and aerobics instructors
3	Actuaries Helpers—painters, paperhangers, plasterers, and	Helpers—painters, paperhangers, plasterers, and stucco masons
4	Purchasing agents, except wholesale, retail, and farm products	Reinforcing iron and rebar workers
5	Budget analysts	Pressers, textile, garment, and related materials
6	Judges, magistrate judges, and magistrates	Helpers—Brickmasons, Blockmasons,stonemasons, and tile and marble setters
7	Procurement clerks	Dining room and cafeteria attendants and bartender helpers
8	Accountants and auditors	Fence erectors
9	Mathematicians	Helpers—roofers
10	Judicial law clerks	Slaughterers and meat packers
11	Education administrators, postsecondary	Landscaping and Groundskeeping workers
12	Clinical, counseling, and school psychologists	Athletes and sports competitors
13	Financial managers	Fallers
14	Compensation, benefits, and job analysis specialists	Structural iron and steel workers
15	Credit authorizers, checkers, and clerks	Cement masons and concrete finishers
16	History teachers, postsecondary	Terrazzo workers and finishers
17	Geographers	Rock splitters, quarry
18	Epidemiologists	Plasterers and stucco masons
19	Management analysts	Brickmasons and Blockmasons
20	Arbitrators, mediators, and conciliators	Roofers

Industry Exposure

AI industry exposure (AIIE) is calculated by accumulating the AI occupational exposure across industries, based upon the concentration of those jobs within a particular industry. Using employment shares at the four-digit North American Industry Classification System (NAICS), a weighted average is applied to the AIOE to derive the AIIE. This construct yields a systematic measure of which industries face the greatest AI exposure.

Table 2 presents the 20 most- and least-exposed industries to AI technologies based upon this methodological approach. Similar to the occupational calculations, industries with the most exposure tend to be the highly educated, white-collar sectors. Financial-sector industry categories — securities, commodities and other investments, along with accounting, tax preparation and bookkeeping — are heavily exposed to AI. This is particularly true for data-driven services, such as investment advice. AI is efficient at analyzing market trends, evaluating performance and using those factors to develop projections of financial asset classes. However, it is likely the most accurate projections would result from combining AI-based projections with the knowledge of seasoned financial market advisors who can intuitively sense the ebb and flow of underlying relationships. Even monetary authorities like the U.S. Federal Reserve might be at risk of losing personnel.

Legal services are the fourth-most exposed field to AI applications. Legal assistants and paralegals are vulnerable because they review oceans of information, synthesizing and sharing it with others through a legal opinion or brief. Other at-risk industries are the IT fields like software publishing, computer-system design, data processing, hosting and similar services. Also included among the most-threatened groups are management training, scientific and technical consulting services, and computer training.

Table 2: AI Industry Exposure (AIIE)

RANK	INDUSTRIES WITH THE HIGHEST AIIE MEASURES	INDUSTRIES WITH THE LOWEST AIIE MEASURES
1	Securities, commodity contracts, and other financial investments and related activities	Support activities for crop production
2	Accounting, tax preparation, bookkeeping, and payroll services	Services to buildings and dwellings
3	Insurance and employee benefit funds	Foundation, structure, and building exterior contractors
4	Legal services	Animal slaughtering and processing
5	Agencies, brokerages, and other insurance related activities	Building finishing contractors
6	Nondepository credit intermediation	Warehousing and storage
7	Other investment pools and funds	Fiber, yarn, and thread Mills
8	Insurance carriers	Support activities for rail transportation
9	Software publishers	Sawmills and wood preservation
10	Lessors of nonfinancial intangible assets (except copyrighted works)	Support activities for water transportation
11	Agents and managers for artists, athletes, entertainers, and other public figures	Logging
12	Credit intermediation and related activities (5,221 and 5,223 only)	Other specialty trade contractors
13	Computer systems design and related services	Waste collection
14	Management, scientific, and technical consulting services	Postal service (federal government)
15	Monetary authorities-central Bank	Highway, street, and bridge construction
16	Office administrative services	Truck transportation
17	Other information services	Apparel knitting Mills
18	Data processing, hosting, and related services	Seafood product preparation and packaging
19	Business schools and computer and management training	Local messengers and local delivery
20	Grantmaking and giving services	Utility system construction

The lowest AI exposure tends to be among blue-collar sectors that involve physical labor. The methodology of focus in this article finds that support activities for crop production is the least exposed category. Services to buildings and dwellings, along with foundation, structure and exterior builders, are the next-least exposed. Others facing minimal exposure include highway, street and bridge construction and other specialty contractors; warehousing and storage; support activities for rail or water transportation; and truck transportation.

Geographic Exposure

Geographic exposure (AIGE) is measured by using the employment shares for individual industries at the county level to create an aggregate weighted total. Alternatively, one could use the AIOE to create the county-level exposure by employing the occupation shares in a specific county.

This systematic, methodological process reveals a geographical exposure that could be described as a layout of the most knowledge-intensive counties across the nation. This map is diametrically opposed to one from 2000 that rated U.S. counties as to their susceptibility to import substitution stemming from China entering the WTO.

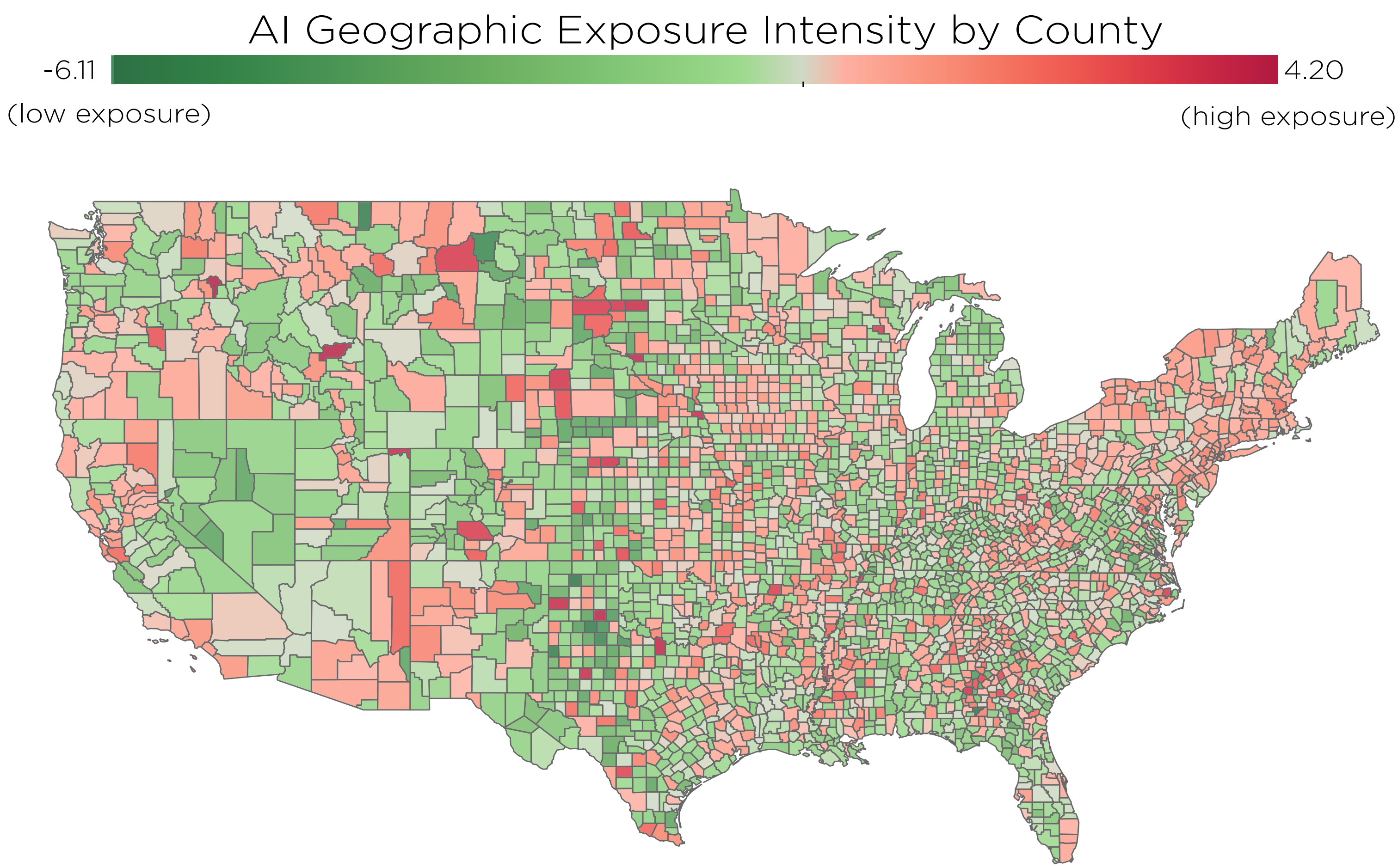
Figure 1 provides a map of county-level job exposure to AI applications. The earlier-mentioned Atlantic corridor is highly exposed to advances in AI, as is the San Francisco Bay area. San Francisco County has an AIGE index of 2.38, closely followed by Santa Clara County at 2.25, while San Mateo County is at 1.65. An AIGE score of 2.0 means a county's exposure is two standard deviation units above the mean of all counties nationwide. New York County — the home of Wall Street and many financial-services firms — has an AIGE index of 2.21. Suffolk County and Middlesex County (Greater Boston) have AIGE indices of 2.11

and 2.02, respectively. In the heartland, Cook County, Illinois (Chicago) stands at 1.28, Hennepin County (Minneapolis) is at 1.73 and Ramsey County (St. Paul) is at 1.61.

Figure 2 displays the AIGE by state. The states most exposed — in order — are Massachusetts; New York; Virginia; Connecticut; Maryland; New Jersey, Minnesota; Washington, D.C.; California; and Utah. Those states with the least exposure — in descending order from 50th — are Nevada; Wyoming; Hawaii; Arkansas; Mississippi; Indiana; Alaska; Kentucky; Idaho; and Louisiana.

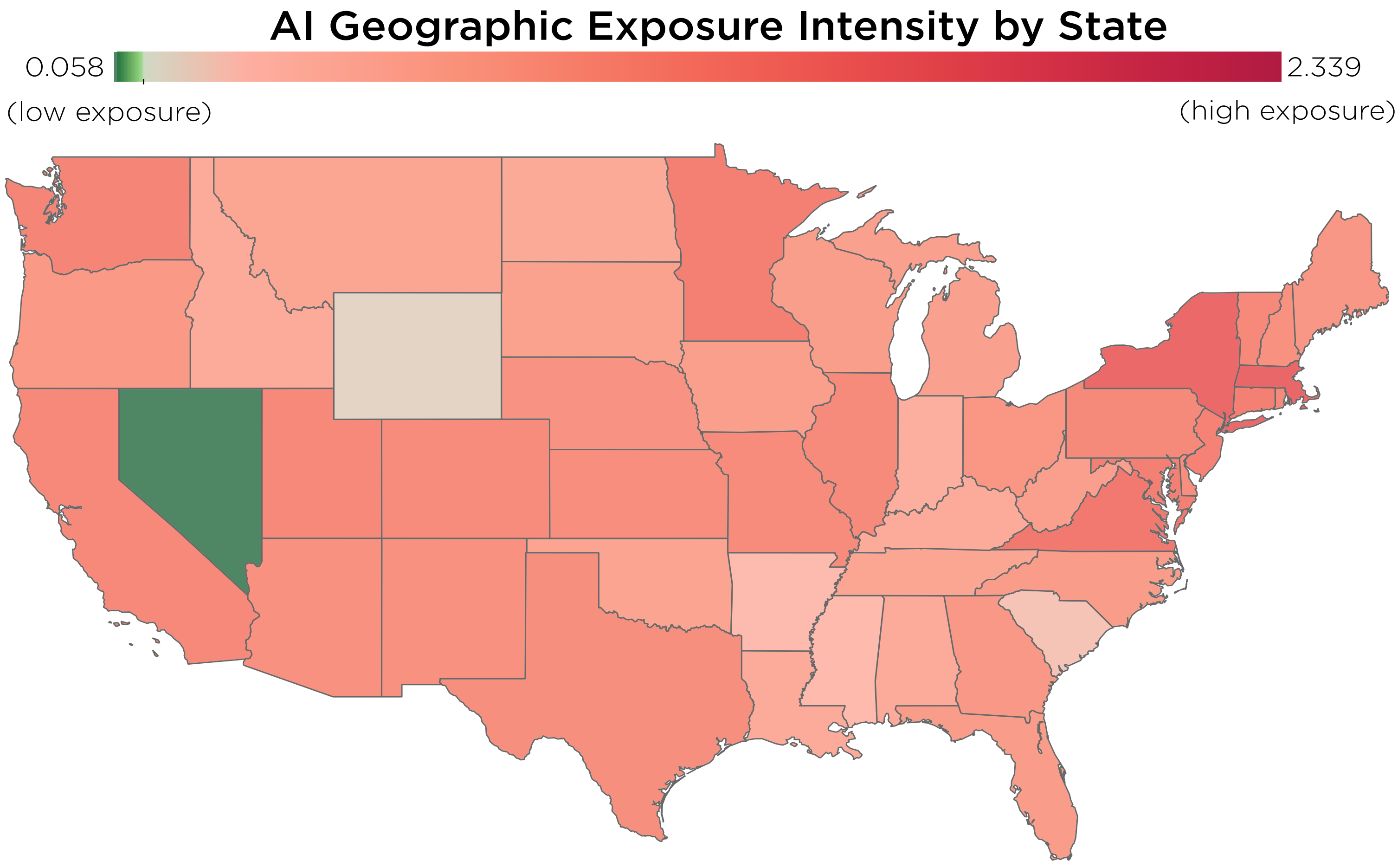
Heartland states are less exposed to AI than others; however, their leaders should not be complacent in attempting to mitigate job losses to AI technology. Opportunities for utilization of AI apps for the heartland will be explored in a forthcoming article, followed by policy options available to limit the negative impacts and derive long-term competitive advantage.

Figure 1: county-level job exposure to AI applications



Source: Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. Strategic Management Journal, 42(12), 2195–2217. https://doi.org/10.1002/smj.3286

Figure 2: AIGE by state



Source: Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. Strategic Management Journal, 42(12), 2195–2217. https://doi.org/10.1002/smj.3286

Note: The state values are population-weighted averages of county values.

ENDNOTES

[1] Hatzius, J., Briggs, J., Pierdomenico, G., & Kodnani, D. (2023). The potentially large effects of artificial intelligence on economic growth. Goldman Sachs. https://www.ansa.it/documents/1680080409454_ert.pdf.

[2] Felton, E., Raj, M., & Seamans, R. (2021). Occupational, industry and geographic exposure to artificial intelligence: A novel dataset and its potential uses. Strategic Management Journal, 42, 2195-2217.

[3] https://www.eff.org/deeplinks/2017/06/help-eff-track-progress-ai-and-machine-learning

[4] https://www.mturk.com/