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Subcommittee on Employment and Workplace Safety
Committee on Health, Education, Labor and Pensions
United States Senate

Hearing on "The Impact of AI on the Workforce"
The AI Workforce PREPARE Act (S. 3339)
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I. Introduction and Qualifications

Chairman Banks, Ranking Member Hickenlooper, and Members of the Subcommittee, thank you for the opportunity to submit this written statement in connection with the Subcommittee's hearing, "The Impact of AI on the Workforce," and specifically on the AI Workforce PREPARE Act (S. 3339).[11]

I am Carol O. Rogers, Director of the Indiana Business Research Center (IBRC) at the Indiana University Kelley School of Business. I am here today as a subject matter expert; the views I express are my own and do not represent my employer, Indiana University.

As Director of IBRC, I work on issues related to Indiana's population, economy, and workforce to help Hoosier policymakers, educators, employers, and workers. In that role, my staff and I work daily with federal statistical series, including data from the Bureaus of Labor Statistics, Census, and Economic Analysis, as well as with Indiana's state administrative records, including unemployment insurance wage records and the state's longitudinal education-to-workforce data system. I have also served on the boards of several national research organizations, including as chairman of national organizations including the Labor Market Information Institute and the Council for Community and Economic Research.

I offer this testimony not as an advocate for a particular outcome on AI policy, but as a researcher with direct, practical experience in the strengths and limitations of the federal and state data infrastructure this bill would rely on. My comments focus on the available evidence showing, as best it can, AI's impact on the workforce, and on whether and where the underlying data infrastructure is ready to support this bill's goals.

II. What We Are Seeing: AI's Impact on the Workforce So Far

Generative and agentic AI has evolved quickly since ChatGPT's public release in late 2022. Adoption has moved from early experimentation to routine business use: nearly 20 percent of U.S. firms now report using AI in at least some business function within the past two weeks (based on the latest data from February 2026), according to the U.S. Census Bureau's Business Trends and Outlook Survey.[1] Individual adoption has grown even faster. Harvard's Project on Workforce finds that 62 percent of U.S. adults ages 18 to 64 now use generative AI, and that 6.3 percent of total work hours are spent using it,[2] building on earlier academic research documenting the pace of generative AI's diffusion into daily work and jobs.[3]

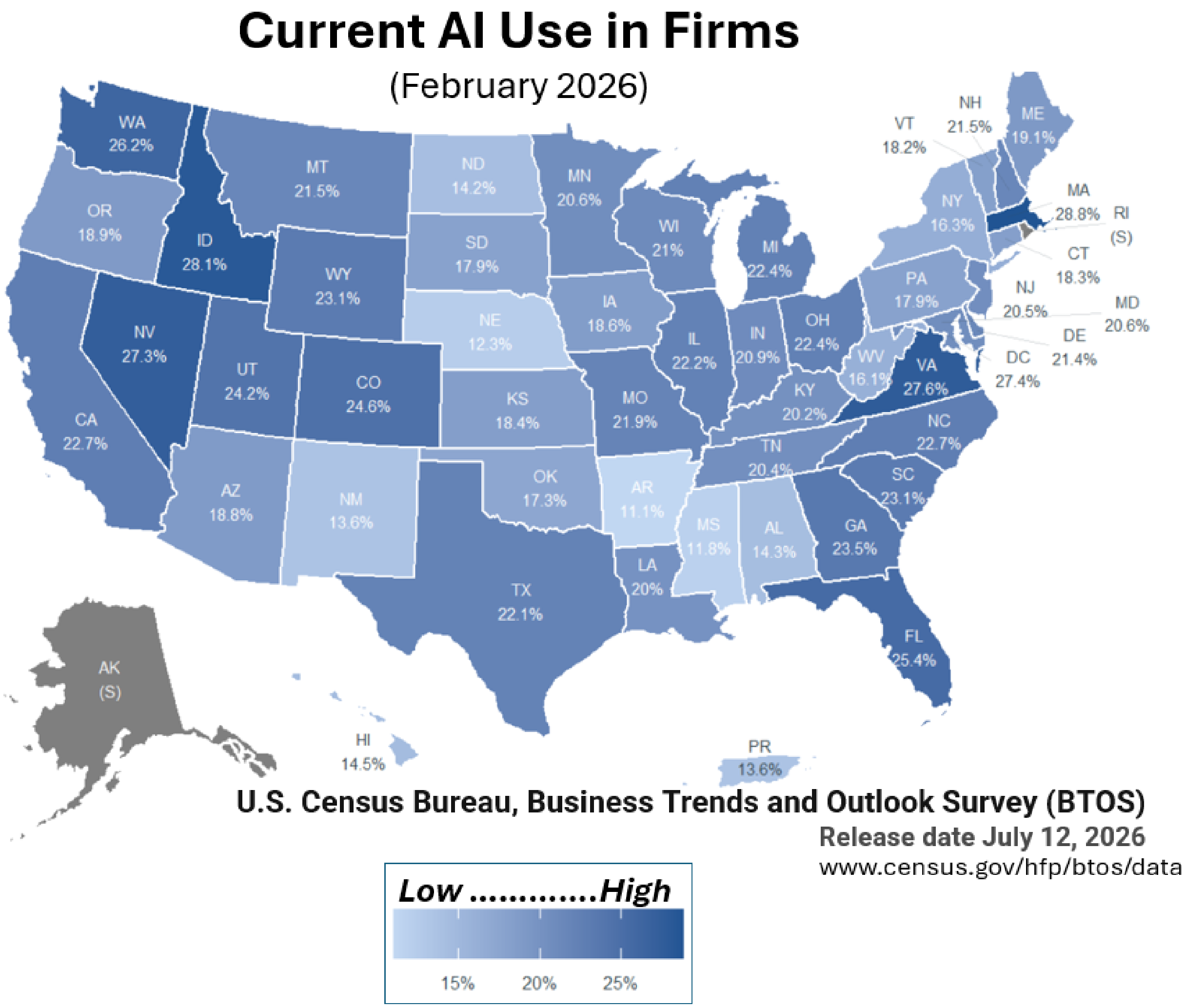

Figure 1. Share of firms currently using AI in some business function, by state, February 2026. Source: U.S. Census Bureau, Business Trends and Outlook Survey (BTOS), census.gov/hfp/btos.

This state-level detail from BTOS, shown in Figure 1, illustrates the unevenness of AI adoption across the country. Current AI use among firms ranges from a low of 11.1 percent in Arkansas to a high of 28.8 percent in Massachusetts, a gap of more than seventeen percentage points. Idaho (28.1 percent), Virginia (27.6 percent), Nevada (27.3 percent), and Washington (26.2 percent) round out the highest-adoption states, while Mississippi (11.8 percent), Nebraska (12.3 percent), New Mexico (13.6 percent), and Alabama (14.3 percent) report the lowest current use. A few patterns stand out. Adoption tends to run highest in states with large technology and professional-services sectors, such as Massachusetts, Virginia, and Washington, or with unusually concentrated industry clusters, as in Idaho and Nevada, and lowest in states with economies weighted toward agriculture and traditional manufacturing, concentrated in the Great

Plains and Deep South. Neighboring states can also diverge sharply: Virginia's 27.6 percent sits beside West Virginia's 16.1 percent, and Idaho's 28.1 percent borders Oregon's 18.9 percent, a reminder that state averages can mask very different local economies just across a state line. Indiana, at 20.9 percent, sits close to the roughly 20 percent national rate cited above, indicating that Indiana's experience is broadly representative of the national middle rather than an outlier in either direction.

My Center recently published research from the Indiana Department of Workforce (In Context, Mar-Apr 2026) comparing occupations with high and low AI exposure.[4] That analysis found job postings in AI-exposed occupations in Indiana shrank 41 percent since 2022, compared to a 35 percent decline in less-exposed occupations. Advertised wages in exposed occupations grew faster over the same period, 16 percent versus 11 percent, and the unemployment-rate advantage AI-exposed workers once held, a full percentage point in 2022, had nearly disappeared by last fall. Taken together, this looks less like mass job elimination and more like market-based repricing: some occupations losing ground, others gaining pay, often within the same broad category.

This pattern is consistent with what we are seeing nationally. The Federal Reserve Bank of Atlanta's survey of more than 700 corporate executives found little near-term aggregate employment decline attributable to AI, alongside a compositional reallocation of labor, with administrative support roles declining as demand grows for skilled technical roles.[5] The Federal Reserve Bank of Dallas has documented a similar wage pattern: nominal wages are up 7.5 percent across all industries since late 2022, but 8.5 percent in the most AI-exposed industries, and nearly 17 percent in computer systems design specifically.[6] Federal Reserve Governor Michael Barr summarized this dynamic in a February 2026 address, noting that AI's long-run effects on the labor market are likely to be positive, but that in the short term it can meaningfully disrupt specific workers, making how we manage the transition consequential.[7]

At the same time, I would caution everyone against inferring too much from Amazon, Meta, and other major technology firms that have announced substantial AI-linked workforce reductions over the past year. Outplacement firm Challenger, Gray & Christmas reports that AI has been cited in roughly a fifth to a quarter of all announced U.S. layoffs so far in 2026.[8] But that pattern is concentrated in a narrow slice of large, capital-intensive technology firms making enormous, simultaneous investments in AI infrastructure. It is not what we see broadly across small and medium-sized businesses. The National Federation of Independent Business's most recent survey finds that 98 percent of small employers currently using AI report no change in their employee counts, and NFIB's monthly economic trends data show small business hiring plans holding at a modest net positive.[9] Policy built primarily around the experience of the largest companies risks missing what is actually happening for the overwhelming majority of American employers.

Finally, a broader macro signal deserves attention. Goods-producing employment declined over the course of last year and has largely plateaued in 2026, even as productivity and wages have continued to rise.[10] Fewer workers producing more value, at higher pay, is consistent with a meaningful contribution from automation and AI, working alongside other factors such as capital investment, though this causal link is not yet provable with the data currently available. It is exactly the kind of signal this bill's data infrastructure should help us track and understand with more precision than we can today.

III. Why Data Infrastructure Will Determine This Bill's Success

The AI Workforce PREPARE Act is, at its core, a data bill. Its central premise, stated plainly in its findings, is that policymakers, training providers, and workers currently lack the data and forecasts needed to anticipate and mitigate AI-driven worker dislocation.[11] I agree with that premise, and the evidence summarized in Section II above illustrates why: the picture is real, but it is also mixed, still emerging, and in places contradictory. Where I would like to focus the Subcommittee's attention is a second-order question the bill does not fully resolve: whether the federal and state data systems it directs agencies to use and improve are themselves currently capable of producing timely, reliable, AI-attributable signals about the labor market.

In my experience, the answer is mixed. Some of the infrastructure this bill would lean on (particularly state administrative wage records), is more capable than is generally understood in federal policy discussions, but underutilized. Other pieces, particularly the timeliness of occupational classification systems and the standardization of employer self-reported data, are not yet fit for the purpose this bill assigns them. Both of these points matter for implementation, funding, and oversight.

IV. Section-by-Section Assessment

A. AI Workforce Research Hub

The bill's creation of an AI Workforce Research Hub to convene researchers, employers, and labor, and to help implement the White House AI Action Plan, is a sound organizing structure. Its value will depend heavily on whether it is designed to integrate existing state and federal data assets rather than to build a new, parallel data collection effort from scratch. States like Indiana have already made substantial investments in longitudinal data infrastructure; a federal hub that does not connect to this work risks duplicating effort and producing a less complete picture than what already exists in pieces across federal agencies and states.

B. WARN Act Amendment — The "Substantial Factor" Standard

Amending the WARN Act to require disclosure when AI is a "substantial factor" in a mass layoff is a meaningful transparency measure, and I understand its intent. However, as a federal data consumer, I want to flag a specific risk: the bill directs the Secretary of Labor to issue guidance on how employers may determine that AI is a *substantial factor* and estimate the associated share of job loss, but employer compliance is explicitly satisfied by a "good-faith statement," without a standardized measurement method attached to it.[11]

Absent a common framework, I would expect significant variation across employers and industries in how "substantial factor" is interpreted, not necessarily out of bad faith, but because there is currently no agreed-upon, operational definition connecting a specific business decision to a specific automation event. This matters because data that cannot be standardized across employers cannot be aggregated into a reliable and comparable national and regional picture, which undercuts the purpose of collecting it and could lead to thousands of differing interpretations.

Recommendation: DOL's guidance should point employers toward existing, standardized classification systems, such as the Standard Occupational Classification (SOC) system and O*NET tasks and skills data, as a reference framework for these determinations, so that reported information is at least structurally comparable across firms, sectors, and states, and can be cross-checked against independent administrative data and other sources over time rather than resting solely on self-reporting.

C. BLS Occupational Forecasts for AI-Sensitive Occupations

BLS occupational projections, and the Standard Occupational Classification system that underpins them, update on multi-year cycles that are considerably slower than the pace at which AI is changing specific tasks and skills within occupations. An occupation can appear stable in the aggregate data long after AI has meaningfully altered the tasks performed within it and the skills required by the worker. I would encourage the Subcommittee to direct BLS toward task-level analysis, for example building on the O*NET task and skills content with more frequent employer surveys, rather than relying solely on occupation-level projections, which are a blunter instrument for this specific policy question.

In terms of resources, in my experience with comparable state and federal data modernization efforts, the anticipated funding over a five-year period is unlikely to be sufficient to meaningfully accelerate BLS's forecasting capacity for such a fast-moving technology. I would recommend the Subcommittee revisit this authorization level as implementation proceeds and consider it a floor rather than an adequate ceiling.

D. Researcher Access to Federal Workforce Data

The bill's provision to increase researchers' access to federal workforce data is, in my assessment, one of its most consequential and most under-discussed elements. Speaking from direct experience navigating Federal Statistical Research Data Center (FSRDC) access, restricted-use microdata agreements, and interagency data-sharing arrangements, I can attest that current approval timelines, inconsistent disclosure review standards across agencies, and limited capacity for linking federal data with state administrative records are all real, practical barriers to timely research, not merely inconveniences.

I would encourage the Subcommittee to seek specificity in how this provision is implemented: whether it means expanded FSRDC access, streamlined restricted-use data agreements, funding for state-federal data linkage infrastructure, or some combination. Without that specificity, this provision risks remaining a statement of intent rather than a change we can actually use.

E. State Administrative Records and In-Demand Occupation Lists

This is the area where I can speak most directly from operational experience, and where I believe the Subcommittee has the greatest opportunity to strengthen the bill.

States' unemployment insurance wage records, together with Statewide Longitudinal Data Systems (SLDS) that link education and workforce outcomes, already capture actual, verified employment and earnings changes on a quarterly basis, at a level of industry and geographic granularity that federal survey instruments cannot match. These records are, in effect, one of the most complete real-time pictures of the American labor market already in existence, and they are collected and maintained by every state, largely independent of federal AI-specific policy. In Indiana, we use these records daily to inform workforce and education policy, and I believe they may be underappreciated in Washington relative to their value.

Two considerations follow. First, I would recommend the bill explicitly direct the AI Workforce Research Hub and related data-collection provisions to connect with, rather than duplicate, this existing state infrastructure, including funding mechanisms for states to modernize and link these records, building on ongoing Enhanced Wage Records initiatives, for AI-workforce intelligence purposes. Second, I want to be candid that data definitions, industry coding practices, and system capacity vary meaningfully from state to state. This is a real and, I believe, solvable technical barrier, but it will require dedicated federal investment and technical assistance to states, not simply a data-sharing mandate, to produce comparable results across states, regions, and even congressional districts in ways that truly inform policy.

Finally, I want to flag the stakes of getting this right: the bill ties AI-informed labor market projections to states' in-demand occupation lists, which in turn determine which training programs receive federal workforce development funding under WIOA and related authorities. This creates a direct chain from federal AI-workforce data quality to aligning which training program an individual worker is funded to attend. Forecast error at the federal level does not stay abstract; it becomes a misallocated training dollar and, for an individual worker, a missed opportunity.

F. Voluntary Public-Private Data Sharing and Prize Competitions

The bill's approach to facilitating voluntary data sharing from AI developers and running prize competitions to better understand AI adoption and task-level automation is a reasonable, low-friction starting point, particularly relative to more prescriptive mandatory-disclosure proposals also pending before Congress. My caution here is methodological: voluntarily submitted adoption data, whether from employers or AI companies, is likely to be subject to selection bias, both in which firms choose to participate and in how they characterize their own AI use. I would recommend that any resulting datasets be explicitly validated against independent administrative benchmarks, such as those described in Section IV.E, rather than treated as authoritative on their own.

V. My Experience in Indiana

My work at IBRC sits directly at the intersection of federal statistics and Indiana's own administrative records, and demand across the state for actionable intelligence on AI's impact is high. At the same time, standardized, complete, current, local data remains hard to come by. Businesses ask us for competitive intelligence. Workers want career and training guidance in an AI-uncertain world. Policymakers want to know whether Indiana will have the workforce employers need. Educators need to align curricula.

We are estimating impact now using AI-exposure metrics by Indiana county, but we still do not know how employers are actually implementing AI, governing its use, integrating it into individual job tasks, or what specific AI skills they are hiring for, training toward, or planning around, the detail we need to gauge impact accurately. This is precisely the kind of employer-level, task-level information the researcher-access and data-hub provisions of this bill could help supply, if implemented with the state-data linkages described in Section IV.E above.

I do not come before this Subcommittee as an advocate for a predetermined conclusion about AI's impact, but as someone whose job it is to make sure Indiana's workers, educators, and policymakers know what is happening, and what is likely to happen, to our workforce.

VI. Recommendations

In summary, I offer the following recommendations for the Subcommittee's consideration as it advances this bill:

1. Direct BLS to prioritize task- and skill-level analysis, building on O*NET, alongside occupation-level projections, given the pace at which AI is changing work within occupations faster than occupational classifications themselves change.

2. Require DOL's WARN Act guidance to anchor employer “substantial factor” determinations to standardized occupational, skill, and task classifications, so reported data can be aggregated and compared across employers and states.
3. Revisit the funding authorization for BLS occupational forecasting as a floor, not a sufficient level of investment, given the scope of the task.
4. Specify what expanded researcher access to federal workforce data will concretely mean in practice, whether FSRDC capacity, restricted-use data agreement timelines, or state-federal linkage funding, rather than leaving the provision as a general statement of intent.
5. Explicitly direct the AI Workforce Research Hub and related provisions to connect with existing state administrative data infrastructure, including UI wage records as part of ongoing Enhanced Wage Records initiatives and Statewide Longitudinal Data Systems, and fund state-level technical assistance to improve cross-state comparability, rather than building new, parallel federal data collection.
6. Require independent validation of voluntarily submitted AI-adoption data against administrative benchmarks before it informs funding-linked determinations such as states' in-demand occupation lists.
7. Direct the AI Workforce Research Hub to develop a standardized instrument for capturing employer-level AI implementation, governance, and skills-demand data, since neither federal nor state administrative systems currently capture this information at the granularity needed to guide training investment.

VII. Conclusion

The bill reflects a sound, bipartisan recognition that this country needs better data to manage the workforce transitions AI is already producing. My purpose today has been to bring a research and data-infrastructure perspective to that effort: to describe what the available evidence currently shows, to highlight where existing federal and state data systems are ready to meet this bill's ambitions, and to flag where targeted investment and design choices will determine whether they can. I would welcome the opportunity to work with the Subcommittee and its staff as this legislation moves forward, and I am happy to answer any questions.

Respectfully submitted,

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[10] U.S. Bureau of Labor Statistics. Employment Situation and goods-producing employment series (CES), 2025–2026, retrieved via FRED, Federal Reserve Bank of St. Louis. fred.stlouisfed.org.

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SUPPLEMENT BEGINS ON NEXT PAGE

Supplementary material appears below that is part of an Indiana Business Research Center working paper looking at AI exposure throughout Indiana, by county. I provide this as further insight into the level of detail sought in my state to understand the breadth of AI potential for employers and workers, as well as noting the potential risks.

Generative AI Exposure Assessment: Indiana Counties

An IBRC Workforce and Economic Development Analysis Working Paper

Indiana Business Research Center, Indiana University Kelley School of Business

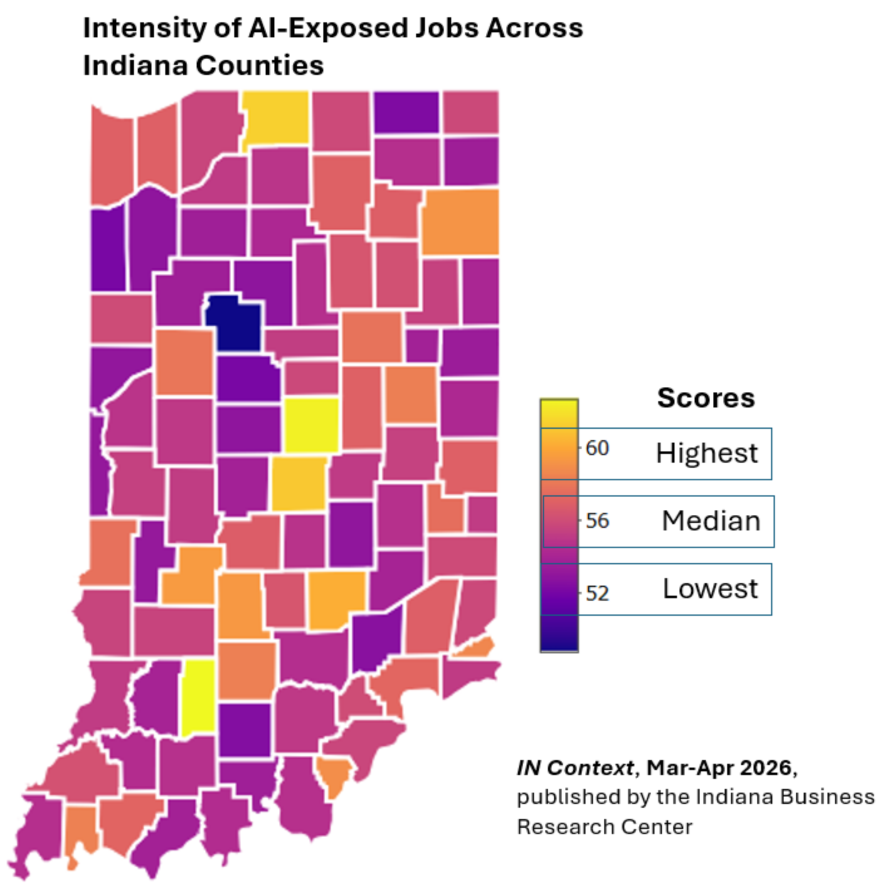

Figure. Intensity of AI-exposed jobs across Indiana counties. Source: IN Context, Mar-Apr 2026, Indiana Business Research Center, incontext.indiana.edu.

The figure above shows the county-level detail behind an estimate of the exposure to Indiana's occupations. Exposure scores cluster tightly across Indiana's 92 counties, ranging from roughly 52 at the low end to 60 at the high end, an eight-point spread, with a median near 56. Most counties fall within a narrow band close to that median, while a handful of counties scattered across both the northern and southern parts of the state register the highest scores on the map, and a single county in the north-central part of the state registers the lowest. This tight, dispersed clustering suggests AI exposure in Indiana is not confined to the state's largest metropolitan counties, but runs at meaningfully similar intensity across metropolitan, small-city, and rural counties alike, underscoring why sub-state, county-level data, and not just statewide or occupational averages, is necessary to guide training investment and workforce policy.

Methodology

Data Integration:

- **Lightcast™ Employment Data:** 2.7 million Indiana jobs across 909 industries.
- **County Staffing Patterns:** Occupation-industry matrices for each county.
- **Felten AI Scores:** Generative AI exposure by occupation and industry.

Key Innovation: Rather than applying generic industry scores, this analysis accounts for county-specific occupational compositions. The same industry can have different AI exposure across counties based on local staffing patterns.

Two types of AI scores are combined to produce a composite score for each county and industry:

- **Image Generation AI Exposure:** measures how susceptible occupations are to being augmented or replaced by AI systems that create visual content, such as DALL-E, Midjourney, or Stable Diffusion. High scores indicate jobs where workers currently spend significant time on tasks like graphic design, illustration, photo editing, or visual content creation that AI image generators can now perform.
- **Language Modeling AI Exposure:** measures exposure to AI systems that understand and generate text, such as ChatGPT, Claude, or GPT-5. High scores indicate occupations involving substantial writing, analysis, research, communication, or information-processing tasks that large language models can augment or automate.

The two scores are combined into a composite AI score, an employment-weighted average of the two types of scores. The full calculation flow:

1. **Occupation level:** each occupation has an image-generation score and a language-modeling score, on a 0-100 scale.

2. **Industry level:** for each county-industry combination, each occupation's AI scores are weighted by its employment share within that industry, and the two AI types are averaged.
3. **County level:** each industry's composite score is weighted by its employment share within the county, producing a final, employment-weighted county score.

These scores measure AI risk: these scores focus specifically on generative AI capabilities that have rapidly advanced over the past two to three years, rather than on traditional automation or robotics. The underlying Felten et al. research identifies which job tasks are most exposed to these newer AI capabilities, providing a more current and relevant assessment of workforce disruption potential than older automation studies. **Complementary coverage:** image generation primarily affects creative, design, and visual-communication roles, while language modeling affects knowledge work, analysis, and text-based tasks. Together, they capture the breadth of generative AI's current capabilities and provide a fuller view of which occupations face the most immediate AI-driven change.

Coverage: 92 Indiana counties, representing 2,790,788 jobs.

Statewide Patterns

There is a strong positive relationship between counties with high language-modeling exposure and high image-generation exposure.

- Most of the low-exposure counties are rural, with the exception of Boone County, which is located in the Indianapolis metropolitan statistical area.
- There are fewer clear geographic patterns among the high-exposure counties, though most are part of metropolitan areas.
- **Martin County** stands out as the county with the highest AI exposure score in the state. This small county's high score is driven by its outsized employment share, approximately 29 percent, in Engineering Services (NAICS 541330), a location quotient of 8.5, an industry with a high image-generation exposure score based on its local staffing patterns.
- **Ohio County** presents a useful counterexample. Given its high employment in hospitality, driven by the Rising Sun Casino Resort, it was surprising that this county also

scored highly on AI exposure. This underlines an important caution for the Subcommittee: these exposure scores should not be relied on blindly for workforce planning. Local knowledge remains essential to interpreting them correctly.

Combining exposure level with county employment size points to a practical, tiered approach for workforce-development priority:

Priority Level	Exposure Tier	Employment Size	Counties
Monitor	Low Exposure	Small	34
Monitor	Moderate Exposure	Small	32
Monitor	Moderate Exposure	Medium	13
Monitor	Low Exposure	Medium	4
Priority 2	Moderate Exposure	Large	4
Priority 1	High Exposure	Large	3
Priority 1	High Exposure	Medium	1
Priority 2	High Exposure	Small	—

Workforce Assessment and Communication

- Conduct skills inventories in high-exposure counties (composite scores above 60) to identify workers in vulnerable occupations.
- Launch public information campaigns explaining AI as a "change multiplier" rather than a job-loss multiplier, emphasizing augmentation over replacement.
- Partner with higher education institutions to assess current curriculum gaps in AI literacy. Indiana University's GenAI 101 course, open to students, faculty, and staff, is one useful model; the Subcommittee and this bill's provisions could help identify how models like it might be extended beyond a single institution's community.

Targeted Support for High-Risk Workers

- Prioritize retraining and upskilling programs for occupations with high AI exposure.
- Focus on counties with both high AI exposure scores and large employment bases for maximum impact, without overlooking more rural areas.

Key insight: the moderate range of county AI-exposure scores, from roughly 48 at the low end to roughly 63 at the high end, suggests Indiana has time to adapt thoughtfully rather than react in crisis mode. This county-level variation offers a roadmap for targeted, regionally informed interventions rather than a one-size-fits-all approach.