AI and the Transportation Workforce

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Introduction

In 2024, the transportation sector contributed 6.7% to the U.S. GDP and served as a linchpin for other key industries, including manufacturing and wholesale (Bureau of Transportation Statistics, 2023). Furthermore, recent geopolitical tensions and trade disruptions have highlighted its critical importance in sustaining global commerce and supporting national resilience. To remain competitive, transportation and logistics firms must accurately map their operations, control costs, and adopt emerging technologies to stay ahead of the curve (Yossi Sheffi, 2025).

Artificial intelligence (AI) has recently evolved from an emerging technology to a general-purpose technology, one with the potential to drive profound changes across industries (Eloundou et al., 2024). In the transportation sector, AI systems are utilized to automate supplier negotiations (Hoek et al., 2022), optimize supply chain management (Rolf et al., 2022), manage customer services (Kang & Choi, 2023), and more. As these capabilities mature and scale, AI offers unprecedented opportunities to optimize operational efficiency. It will also change the nature of jobs.

In this report, we aim to address executives, practitioners, and policy-makers in the field of transportation's most pressing question about AI and the workforce:

How will AI impact the transportation workforce, what will be the financial consequences, and which parts of the workforce will be most affected?

To address this question, we introduce a novel methodology that breaks down jobs into their elemental units: tasks. For each task, we evaluate its cost and assess its suitability for replacement by an AI-based system. This task-based framework enables a precise mapping of AI's impact across roles, organizations, and sectors.

We conducted this work at the MIT Center for Transportation & Logistics, where our research focuses on the intersection of artificial intelligence, labor economics, and supply chain management. This report provides data-driven insights to inform strategic decision-making on the impact and investment in AI for the transportation sector.

In this report, we:

A. Analyze and provide insights on the evolution of the U.S. transportation workforce over the last 10 years.

B. We introduce a new methodology to dynamically assess the impact of AI at the task, job, and sector levels.

C. We share findings from applying this approach to the transportation sector.

Our analysis considers the workforce through three lenses: (1) Human impact, job volumes and employment trends, (2) Financial impact, wage exposure and labor cost optimization, (3) Educational impact, vulnerability and resilience by education level.

A.1 Workforce Review
Employment

14.9 Million
Number of workers in logistics-related sectors in the US workforce.

Broader Logistics Employment

- In 2024, the logistics-related sectors encompassed 51 unique job roles and employed a total of 14.9 million workers.
- 5.1 million of the jobs (34%) are exclusive to the transportation and warehousing sector.
- The remaining 9.8 million (66%) include logistics occupations (such as mechanics) that exist in other sectors (e.g., manufacturing) and are not exclusively classified under transportation and warehousing.

7.1%
Broader logistics' employment CAGR between 2015 and 2024.

Employment Growth

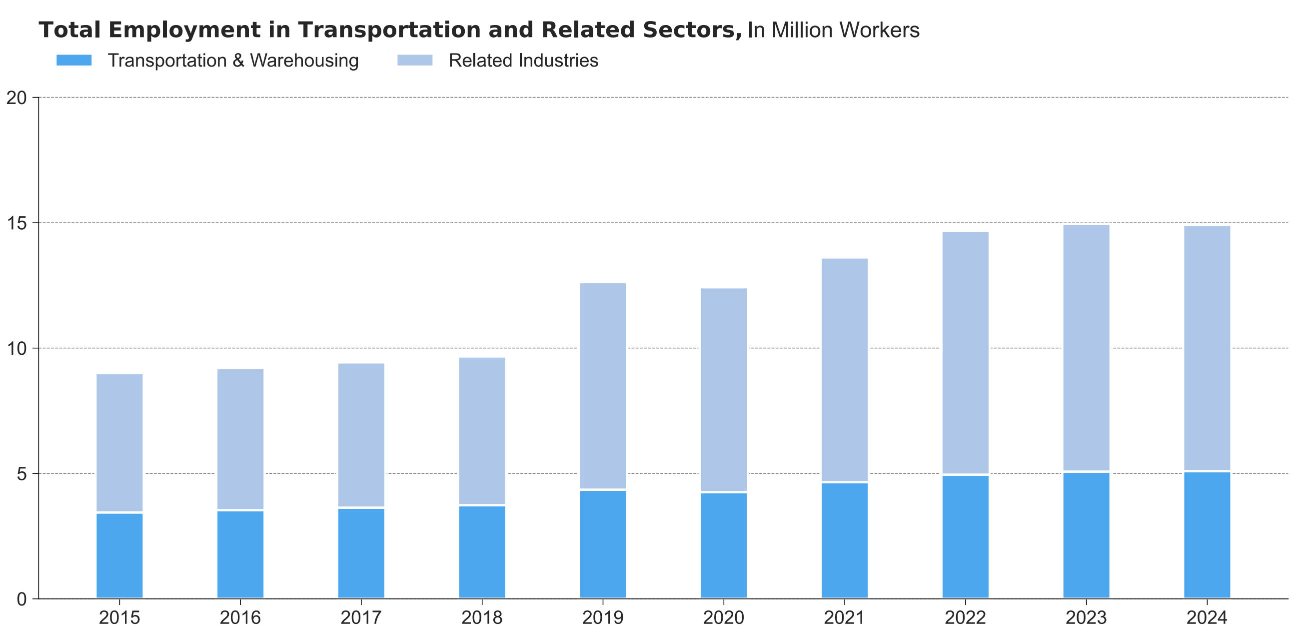
- Demand for labor in the U.S. transportation sector rose from 3.4 million in 2015 to 5.1 million in 2024, reflecting a compound annual growth rate (CAGR) of 4.5%.
- Employment in "other logistics" industries grew from 5.5 million in 2015 to 9.8 million in 2024, reflecting a CAGR of 7.1%.

2024
First year since the COVID-19 pandemic with decreasing employment

Changes in Trend

- Overall transportation-related employment peaked at 14.95 million in 2023.
- Broader logistics' employment showed a slight decline of 0.3% (a loss of 46,000 jobs) in 2024, marking the first contraction since the onset of the pandemic crisis.

Exhibit 1 – Logistics and related sectors' employment from 2015 to 2025.



Sources: Occupational Employment and Wage Statistics (OEWS), U.S. Bureau of Labor Statistics, 2024; O*NET Database, U.S. Department of Labor, 2024.

A.2 Workforce Review
Salaries and Wage Bill

Narrowing the focus to the transportation and warehousing sector, we analyze salaries from 2015 to 2024, a period during which the sector's workforce grew from 3.4 million to 5.1 million workers.

290.4 Billion

Total wage bill in the transportation and warehousing sector

Wage bill

- The wage bill is calculated by multiplying the number of workers per job by their average salary.
- The aggregate total wage bill rose from $140.8 billion in 2015 to $290.4 billion in 2024 (106.2 percent cumulative growth; ≈ 8.4 percent CAGR).

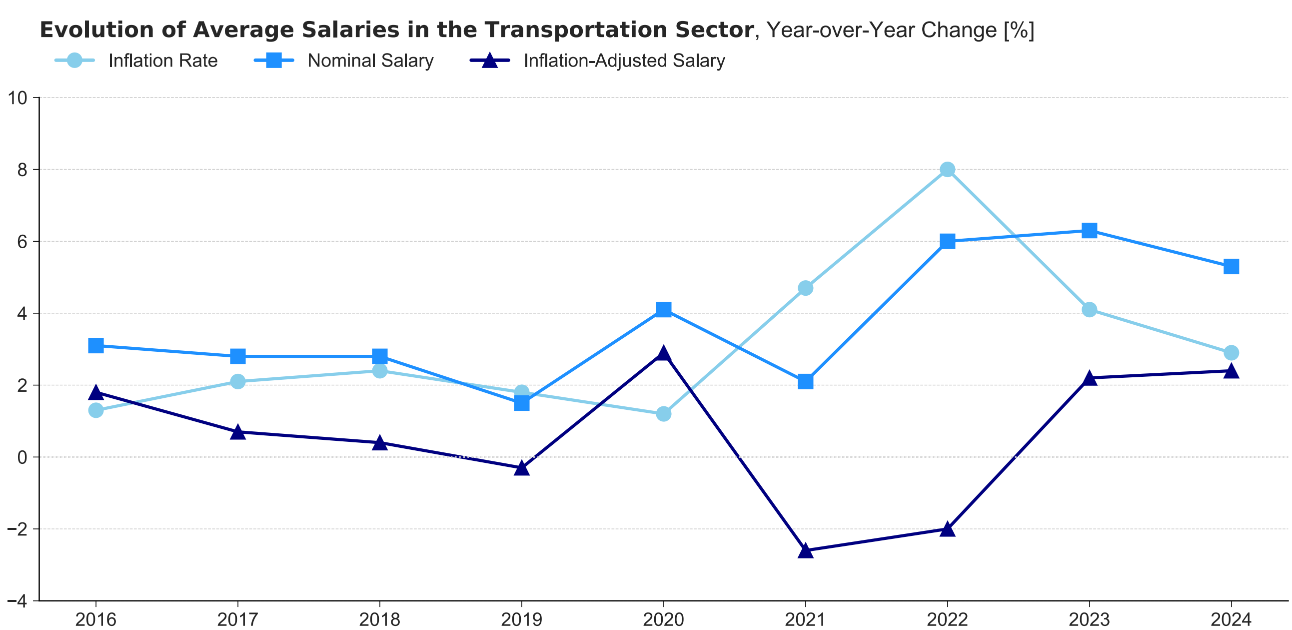
0.9%

Inflation-adjusted average annual wage increases YoY from 2015 to 2024.

Changes in wages

- The average annual salary increase is 3.8 percent per annum.
- Adjusting for inflation (averaging 2.9 percent p.a.), the average annual salary increased by 0.9 percent per annum.
- This highlights that the total wage bill increase primarily stems from the rise in workforce size rather than substantive gains in real earnings.

Exhibit 2 – Median Transportation Salary and Inflation Growth (2016–2024).



A.3 Workforce Review
Education

We focus on the transportation and warehousing sector, providing insights into the distribution of education levels of workers from 2015 to 2024.

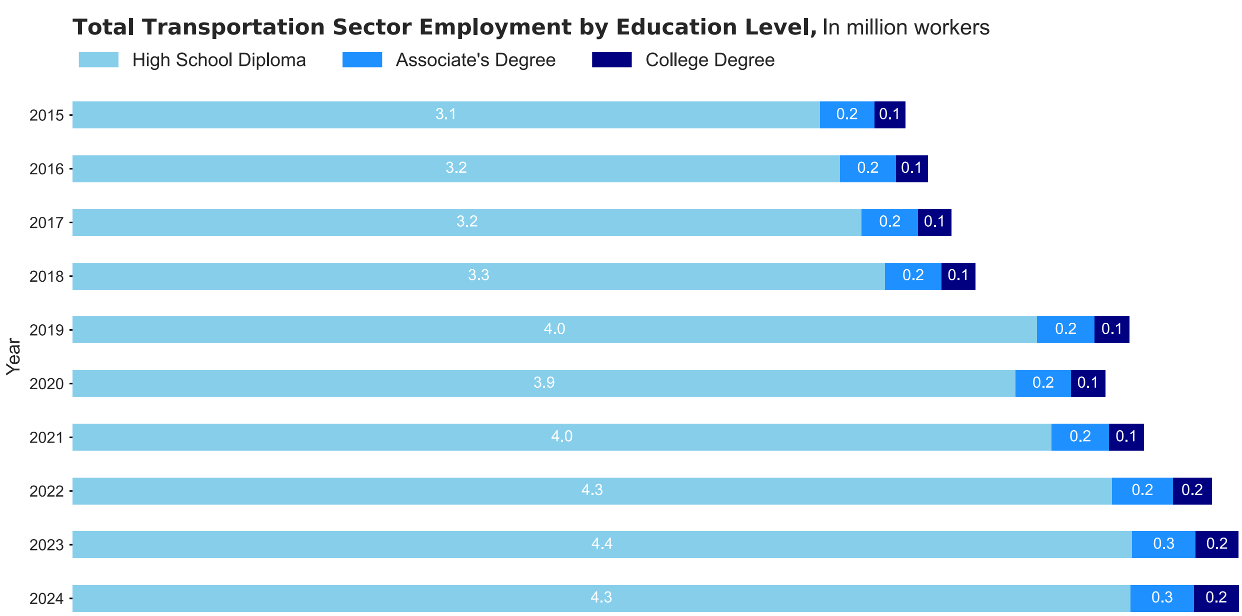
Education levels in the workforce

- The rise in workforce size, particularly among those with high school qualifications and on-the-job training, was the primary driver of the workforce increase in the transportation and logistics sector. This segment grew from 3.1 to 4.3 million workers (41% over 10Y, 3.3% CAGR).
- Associate degree qualified workers volume grew from 0.22M to 0.26M (16.5% over 10Y, 1.7% CAGR)
- The number of college degree-educated workers grew from 0.13M to 0.18M (44% over 10Y, 3.3% CAGR).

Change in demand for workers' education level

The COVID-19 pandemic affected all levels of education. In contrast, the 2024 workforce contraction primarily affected workers with high school and associate's degrees (-0.1%), while the demand for workers with college degrees rose at a rate of 5%, representing a slight increase over the sector's typical growth.

Exhibit 3 – Employment growth rate for associate's degrees has been lower compared to high school diplomas and College degrees.



Note: Education levels are not provided for generic employment titles "All other", explaining the difference in the sector's employment numbers from page 2.

B.1 Methodology

Jobs as Tasks

A common framework in labor-economics research represents jobs as collections of tasks (Autor et al., 2003).

To implement this framework, we utilize the U.S. Department of Labor's Occupational Information Network (National Center for O*NET Development, 2025), which reports a detailed list of tasks based on the frequency with which workers perform them for each job and categorizes them by sector.

We treat task frequency as a proxy for the allocation of a worker's time dedicated to each task. This approach assumes that each task requires a comparable amount of time for a 'typical' worker in that occupation (Martin, 2022; Brandes & Wattenhofer, 2016).

Full-time equivalent (FTE)

An FTE converts task time shares into the equivalent number of full-time workers. For example, if a task occupies 25% of a worker's time, that equals 0.25 FTE. Summing across all employees in an occupation tells us how many full-time workers would be required to cover that task.

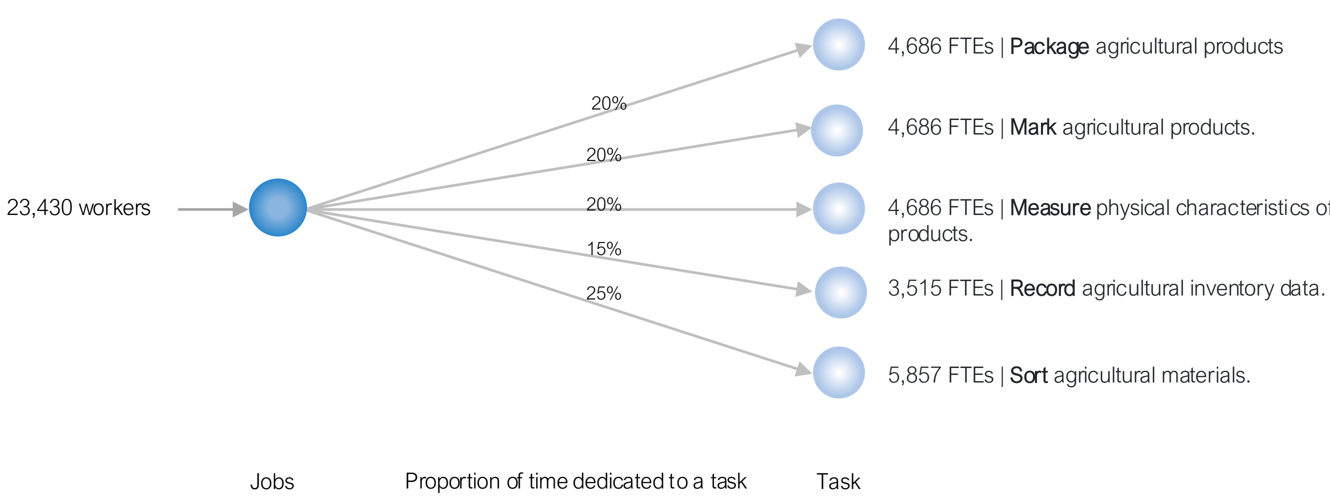
Task Annual Wage Bill

To evaluate the annual wage bill of each task, we multiply its FTE total by the occupation's average yearly salary. For instance, if a task represents 10 FTEs and the average salary is $80,000, the task's annual wage bill is $800,000.

Task Wage Bill and FTE Across Occupations

Many tasks appear in multiple occupations. By aggregating a task's FTEs and wage bills across all relevant jobs, we can estimate the total labor cost dedicated to that task workforce-wide.

Exhibit 4 – Example with the "Graders and Sorters, Agricultural Products" job represented as a set of tasks.



B.2 Methodology
Exposure of Tasks to AI

Artificial intelligence (AI) refers to systems capable of learning from data to perform tasks that generally require human intelligence. AI encompasses a broad set of approaches, including symbolic logic, machine learning, and neural networks, and is increasingly recognized as a general-purpose technology with applications across a wide range of sectors and jobs (Eloundou et al., 2024).

AI can increase the productivity of workers on specific tasks by either complementing or replacing them, a concept known as task exposure to AI (Felten et al., 2018).

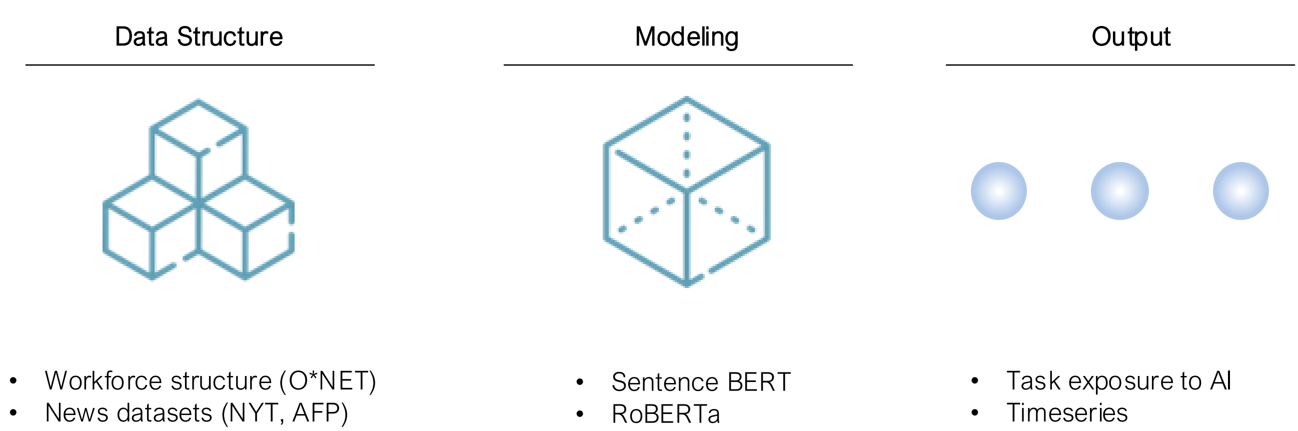
While this topic has received growing attention, most existing approaches rely on expert judgment and provide static snapshots that quickly become outdated (Brynjolfsson et al., 2018; Felten et al., 2021; Frey & Osborne, 2017).

To address this gap, we built on the work of Webb (2019) to develop a dynamic framework that uses machine learning to extract and process information from news articles in real-time. We applied machine learning techniques to news media as a proxy for the societal zeitgeist, capturing how AI adoption is perceived and discussed in practice. To mitigate bias from sensationalism and partisanship, we applied sentiment analysis that favors neutral articles and verified our results with two independent data sources (Liu et al., 2019; Reimers & Gurevych, 2019).

Our working paper demonstrates that this approach aligns with established metrics while offering a scalable and continually updated perspective on AI's impact on work (Bouquet & Sheffi, 2025).

Using task exposure and considering that we know the time dedicated to each task within a job (page 6), we obtain the job's AI exposure by calculating a weighted average of its tasks' exposure (Bouquet & Sheffi, 2025).

Exhibit 5 – Illustration of the dynamic framework to evaluate the exposure of a task to AI.



B.3 Methodology
Specific Sector Analysis

Jobs as Tasks

In Bouquet and Sheffi (2025), we applied our AI exposure framework to the entire U.S. workforce, modeling 110 million workers on more than 2,000 tasks, 900 occupations, and 20 industries. We used two years of news articles from The New York Times (NYT) and Agence France-Presse (AFP) to obtain an AI exposure score in 2024 for each of the 2,000 tasks evaluated. The time dedicated to each task within a job was used to evaluate a job's AI exposure score.

We labeled tasks and occupations as highly exposed to AI if their exposure scores exceed the third quartile (75th percentile) of the global AI exposure score distribution (Pew, 2023). We calculate these quartile thresholds separately for tasks and occupations (jobs) across the whole dataset.

The Transportation Workforce

To narrow our analysis to the Transportation and Warehousing industry, we filtered our dataset to include only jobs and tasks within this sector.

Finally, we considered each occupation and its constituent tasks using our Full-Time Equivalent (FTE) methodology. For each task, we report its FTE count and annual wage bill based on Transportation and Warehousing employment data. As well, we report AI exposure score based on the media articles.

Scalability & Extensibility

Although we apply our approach to the Transportation and Warehousing workforce as a whole, this framework can be applied to any labor market or organization, whether at the level of a single company, an entire industry, or a geographic region (such as a city, state, or country). It is equally adaptable to other sectors, use cases, and time horizons, enabling consistent task and job-level cost structure and AI exposure analysis.

C.1 | Results
Employment

The question we are aiming to answer is:

”How many workers in the transportation workforce will be impacted by AI?”

1.1 Million

FTE of tasks with high acceleration potential.

AI Acceleration of Tasks

- We identified 186 tasks out of the 990 in the Transportation sector that could be significantly affected by AI.
- These tasks represent 1.1 million FTE across the transportation sector.

83%

Percentage of transportation jobs where AI could accelerate at least one task.

AI Impact on Jobs

- Out of 51 jobs, we identified 18 with significant vulnerability scores; a sample of which is depicted in Exhibit 6. These jobs involve tasks that AI could impact. However, no job has all its tasks significantly exposed. This suggests that AI can complement and make workers more efficient, rather than completely replace them.
- Out of the 51 jobs in the transportation sector, 44 perform at least one task with a high vulnerability score. This indicates that AI could impact 4.2 million (83%) of workers at large.

Exhibit 6 – Sample of tasks and jobs identified wit

High AI Vulnerability – Task	FTEs
Review work orders or schedules to determine operations or procedures.	92,000
Verify information or specifications.	88,000
Receive information or instructions for performing work assignments.	82,000
Read maps to determine routes.	76,000
Prepare documentation for contracts, transactions, or regulatory compliance.	64,000
Monitor cargo area conditions.	60,000
Total	1,100,000

High AI Vulnerability – Jobs	Number of Workers Impacted
Shipping, receiving, and inventory clerks	111,000
Reservation and Transportation Ticket Agents and Travel Clerks	95,000
Cargo and freight agents / Freight Forwarders	89,000
Dispatchers, except police, fire, and ambulance	84,500
Weighers, measurers, checkers, and samplers, recordkeepers	10,750
Couriers and messengers	7,000
Total	2,500,000

C.2 | Results
Salaries and Wage Bill

We concentrate on tasks where AI can greatly enhance efficiency and focus on answering the following:

"What is the impact of AI on the wage bill of the transportation sector?"

$ 290 Billion

The total annual wage bill of the transportation sector in 2024.

Current Wage Bill

- In 2024, the transportation sector contributed $1.8 trillion in annual value added.
- Labor accounted for approximately $257 billion of that amount.
- Labor costs account for approximately 14% of the sector's GDP contribution and 0.9% of the US total GDP.

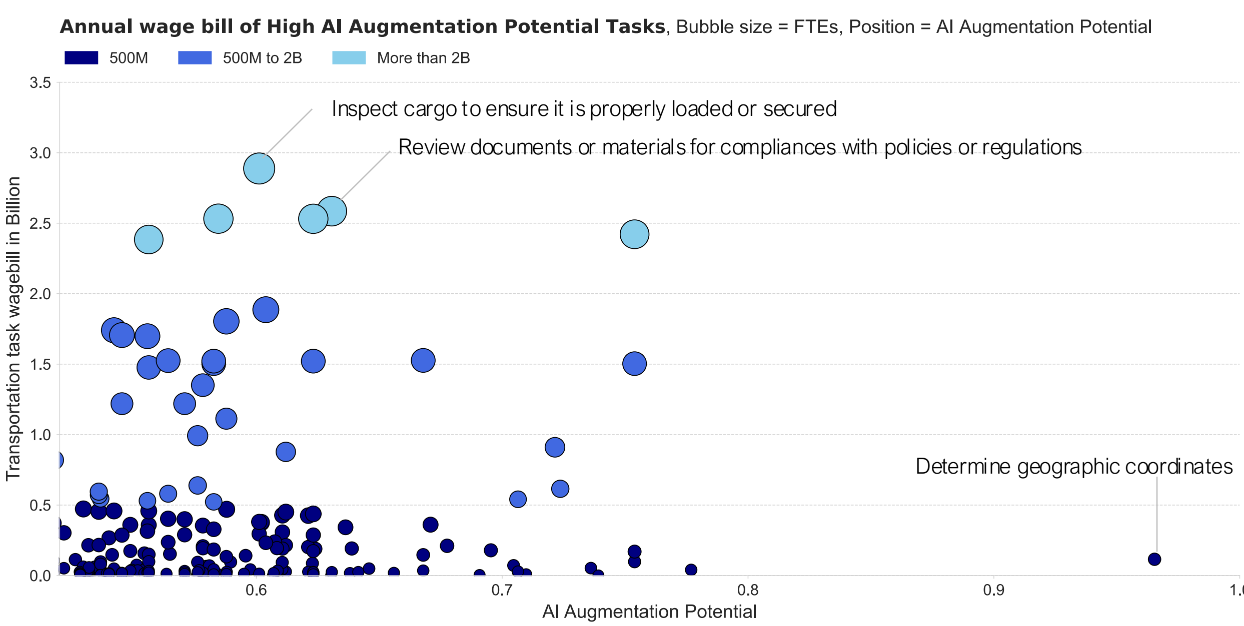
$65 Billion

The annual wage bill of tasks that AI could significantly accelerate.

AI Wage Bill Impact

- The annual wage bill for the 186 tasks exhibiting high AI vulnerability amounts to approximately $65.5 billion.
- Not all tasks carry the same weight in terms of labor cost:
  - Six specific tasks are projected to incur an annual Full-Time Equivalent (FTE) labor cost exceeding $2 billion.
  - Thirty-four tasks are anticipated to have an annual labor cost surpassing $500 million.

Exhibit 7 – Targeted efforts to implement AI in transportation can be strategically aligned to enhance operational efficiency by focusing on tasks with a high wage bill.



C.2 Results
Salaries and Wage Bill

We concentrate on tasks where AI can greatly enhance efficiency and focus on answering the following:

"What is the impact of AI on the wage bill of the transportation sector?"

While AI can perform tasks more efficiently, it is essential to consider the following
- AI may not completely replace tasks, but it can augment workers' productivity.
- The increased productivity from AI can free time for workers to focus on other tasks (thereby allowing fewer workers to perform certain jobs or allowing for more work to be performed).

Targeted AI Deployment and Scenario Simulation

- We consider multiple AI deployment scenarios, focusing on tasks with high AI vulnerability score and their wage bills.
- A study by Dell'Acqua et al. (2023) found that workers using AI completed tasks 25% faster and with higher-quality results. We consider three levels of productivity increase: 5%, 15%, and 25%.
- We implement each productivity scenario with a different task selection cutoff based on wage bills. The results are presented in Exhibit 8.

As depicted there, targeted AI implementation for just six tasks can yield $800 million across the entire sector in our conservative scenario and up to $4 billion in the BCG scenario, with a 25% productivity increase.

Exhibit 8 – Targeted AI Implementation

Task Minimum Annual Wage Bill – $2 Billion+ Tasks

Number of tasks	Scenario 5%	Scenario 15%	Scenario 25%
6	0.8 Billion	2.3 Billion	3.8 Billion

Task Minimum Annual Wage Bill – $500 Millions+ Tasks

Number of tasks	Scenario 5%	Scenario 15%	Scenario 25%
34	2.4 Billion	7.1 Billion	11.9 Billion

Task Minimum Annual Wage Bill – Any Task

Number of tasks	Scenario 5%	Scenario 15%	Scenario 25%
186	3.3 Billion	9.8 Billion	16.4 Billion

C.3 Results
Education

"Which levels of education are most exposed to AI capabilities?"

The Two Faces of AI Exposure: Accessibility vs. Specialization

It's important to understand that a job labeled as "exposed to AI" is not necessarily at risk of being eliminated. Instead, exposure to AI signals a transformation of jobs' structures rather than complete displacement (Autor & Thompson, 2024). While task automation leads to increased productivity, its effects on employment and wages can materialize in two different ways:

- When expert tasks are automated, the job becomes more accessible to less-qualified individuals. The barrier to entry lowers, which can result in increased employment, but often at the cost of stagnating or declining wages, as the average required expertise diminishes.
- When routine or mundane tasks are automated, the job becomes more specialized, increasing the need for higher expertise. This tends to result in wage growth for those who remain in the role, though employment levels may stagnate or decline as fewer individuals are qualified to perform the remaining, more complex tasks.

Exhibit 9 – How Task Automation Reshapes Jobs: A Dual Perspective (Autor & Thompson, 2024)

	Expert Tasks Automated	Mundane Tasks Automated
Labor Productivity	Increase	Increase
Average Expertise	Decrease	Increase
Employment	Increase	Stable or Decrease
Wages	Stable or Decrease	Increase

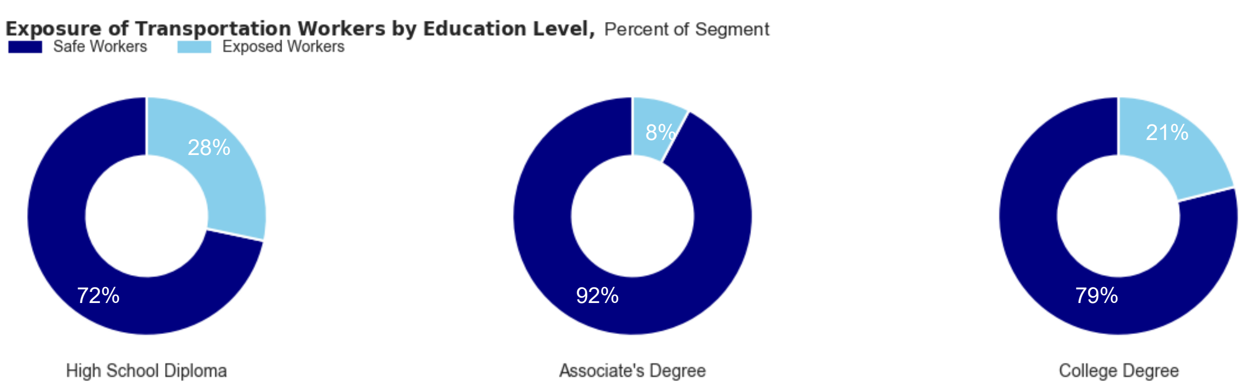
C.3 Results
Education

”Which levels of education are most exposed to AI capabilities?”

Potential Impact of AI on the Transportation Workforce by Education Level

- Transportation industry workers with only a high school diploma face the highest exposure to AI. Approximately 28% of their jobs fall within the top quartile of AI-exposed occupations, representing around 1.1 million workers in the United States. These roles typically have low barriers to entry, making them particularly vulnerable to displacement if a rise in demand does not outpace productivity gains from automation. Without new job creation or reskilling efforts, the number of workers in this segment and their wages are likely to decline.
- In contrast, workers with an Associate’s Degree face the lowest AI exposure, with only 8% of their jobs categorized as highly exposed, affecting roughly 20,000 positions. However, due to the diverse nature of these roles, predicting wage and employment trends requires analysis at the job level rather than generalizations by education alone.
- For workers with a college degree, 21% of jobs, or 37,000 workers, are classified as highly exposed to AI. The future of these roles depends on the nature of the tasks being automated. If expert tasks are automated, such jobs may become more accessible to a broader talent pool. Conversely, if routine tasks are automated, the remaining responsibilities may become more specialized, which can increase wages but also reduce overall employment.

Exhibit 10 – The percentage of workers exposed to AI by education level



Conclusion

The transportation sector plays a vital role in the U.S. economy, supporting a workforce with an annual wage bill of approximately $290 billion. Our analysis indicates that advances in artificial intelligence could have a significant impact on the workforce in the industry, potentially affecting tasks comparable to those performed by approximately 1.1 million full-time workers. The economic implications of AI adoption range from a conservative estimate of a billion-dollar reduction in wage bills to a more aggressive scenario with potential losses of up to $16 billion.

The current employment downturn in the sector, the first since the COVID-19 pandemic, is likely influenced by broader economic conditions, such as the persistent freight recession and normalization of demand after pandemic-era highs, rather than the immediate effects of AI. However, as the industry pivots toward AI integration, particularly within small and medium-sized enterprises that adapt to technology at a slower pace, the potential for disruption remains significant.

While the total wage bill in the transportation sector has grown steadily, tasks highly exposed to AI account for approximately $65 billion of total wages. Although complete automation is unlikely, our focused analysis of the six largest exposed tasks in terms of wage bill indicates potential annual cost reductions of between $1 billion and $4 billion, contingent upon widespread adoption of technological advancements such as autonomous trucking and the development of AI systems to automate clerical tasks.

The workforce's composition reveals a concerning vulnerability. With about 4.3 million workers holding lower educational qualifications (high school or less), this segment is particularly at risk, as we estimate that 28% of these jobs fall into the highest category of AI exposure. While total job elimination is unlikely, the impact of AI-driven productivity gains, combined with stable demand, may result in reduced wages and fewer employment opportunities.

To mitigate these effects, targeted reskilling initiatives and policy interventions will be crucial in supporting affected workers and ensuring that the benefits of AI advancements are shared across the sector. Addressing these challenges will be crucial to safeguarding the livelihoods of workers and maintaining the economic vitality of the transportation sector in a rapidly evolving landscape.

Learn More

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