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To What Extent Does Industry-Level Exposure to Generative AI Influence Wage Growth Trend in the U.S. Service-Sector Industries During the Early Adoption Period (2023–2025)?

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ABSTRACT

This paper investigates the impact of GenAI on the US labour market, especially in the service sector based industries with varying level of exposure, during the critical early adoption window of January 2023 till January 2025. The impact is measured in terms of relation between industry level exposure and growth in realized wage. Based on the data of Pew Research and Stanford HAI, this paper develops an AIOE (Artificial Intelligence Occupational Exposure) index and collects hourly wage data from the Bureau of Labour Statistics across ten service sector based supersectors to conduct a cross-sectional econometric analysis.

Based on the empirical findings from the research, there is a statistically significant positive correlation with $r = 0.996 \wedge p < 0.001$. Ordinary Least Squares (OLS) regression modeling reveals that every percentage increase in the industry-wide AI exposure of the workers, there is an approximate0.103 percentage point increase in hourly wage growth rate. This findings reveal a major divergence from the historical trends of automation led impact on workforce that included labour substitution and wage suppression. GenAI led automation rather functions as a cognitive force multiplier that augments productivity of labour in high exposure sectors with majority of tasks based on cognitive functions. This paper concludes by establishing a positive correlation between AI exposure and wage growth, but also reveals a structural divide growing between cognitive-intensive and manual-intensive service roles that creates an urgent need for reskilling and upskilling in the field of AI skilling.

Keywords: Generative AI, Wage dynamics, Labour Economics, General Purpose Technology, AI Exposure, LLM

INTRODUCTION

As the OpenAI released ChatGPT to the public in November 2022, it marked a paradigm shift in the global economy as Artificial Intelligence transitioned from a specialized computational tool to a 'General Purpose Technology' (GPT), a characteristic shared by technological landmarks like the invention of steam engines, electrification, and the internet. Such technologies are ubiquitous in nature, and their continuous improvement allow for complimentary inter-sectoral innovations (Brynjolfsson et al., 2023). However, the economic target of AI as a GPT is very distinct from the historical trends.

A historical pattern shows that automation leads to 'routine-based technological change' (RBTC). Whether it be the 19th century innovation of mechanical looms or the 20th century innovation of mechanical arms, these are the routine manual tasks that undergo transformation. Although these transformations changed the nature of manufacturing jobs and hollowed the middle-income groups involved in these activities, the service sector jobs were largely insulated from threats of automation with cognitive flexibility and processing of complex language considered safe from algorithmic substitution (Acemoglu & Restrepo, 2018). However, the emergence of generative AI challenges this historical trend as the Large Language Models (LLMs) reduce the marginal cost of cognitive functions, and subject the high skill labour market or 'knowledge workers' like coders, legal analysists, and writers to massive uncertainties.

With the LLMs increasingly being integrated with the workforce, the relation between technology and labour has come under fresh scrutiny with debates centered around substitutive or complementary relation between technology and labour. These debates largely revolve around The Displacement Hypothesis and the Productivity Hypothesis. Based on 'Task Based Approach', the Displacement Hypothesis proposes that capital will substitute labour once Generative AI becomes capable of performing cognitive tasks like drafting emails or summarizing data at a faster and cheaper rate than humans. Based on estimations by Goldman Sachs (2023), AI automations threaten almost two third of existing jobs, creating demand shock in the labour market. On the other hand, the Productivity Hypothesis proposes alleviation of human intellectual functions through AI, within the framework of 'Skill-Based Technological Change' (SBTC). By

handling the repetitive cognitive functions, AI facilitates increased allocation of human efforts towards high-value strategic tasks that increases Marginal Revenue Product of labour (MRP_L) and, a theoretical consequence, their wages (Autor, 2015).

Although there is abundance of theoretical models predicting impact of this massive technological shift, there is a scarcity of empirical evidence. A key limitation in the existing research is that either they focus on employment quantities in terms of loss vs. creation of jobs or use pre-2023 forecasts. There has not been much research focused on early adoption period of 2023 to 25, a critical period to analyze the impact of AI on realized wage trends. This timeframe offers a critical opportunity to assess whether AI exposure leads to devaluation of labour as commodity or appreciation as more premium assets.

This study aims to address this research gap through quantitative analysis of relation between AI exposure of a particular job and the realized wage growth. Guided by this aim, this research paper investigates: To what extent does Generative AI exposure correlate with wage trends across US service industries between 2023 and 2025.

Through analysis of wage growth variance across a set of industries with varying levels of AI exposure, this paper attempts to provide an empirical understanding of whether the US service economy is dominated by 'Displacement' or 'Productivity' effect of Generative AI.

LITERATURE REVIEW

One of the key focusses of modern economics is the study of how technological innovation interacts with the labour market dynamics. Although there has been a framework to understand the impact of automation, based on historical shifts from industrial revolution to the rise of computer technology, the advent and subsequent growth of generative AI (Gen AI) poses unique challenges to this theoretical framework. This review provides a critical examination of existing literature from four perspectives- a shift from 'routine-based' to 'cognitive-biased' functions, the competing theoretical perceptions of automation as means of labour displacement or labour augmentations, the emerging evidences of Large Language Models (LLMs) creating skill-levelling effect in specific areas, and methodological limitations in quantification of 'AI exposure'.

2.1 Historical context:

Routine-Biased Technological Change (RBTC) hypothesis has been the most commonly accepted framework for understanding impact of automation for the last four decades. 'Task-Based Approach', formalized by the pioneering work of Autor, Levy, and Murnane (2003), demonstrated the substitution effect of computerization for routine tasks like calculation, sorting or filing that require explicit and codifiable rules, and complementary effect on non-routine abstract tasks.

This framework is used for further documentation of labour market polarization by Goos and Manning (2007). Their findings, based on analysis of labour markets in the US and the UK, showed a hollowing of middle class as the mid-skill based clerical and manufacturing jobs witnessed a decline in demand. On the other hand, demand for high-skill based jobs like management and creative roles witnessed rise in demand, along with low-skill jobs like food preparation, cleaning and similar manual tasks. Under the RBTC framework the service sector remained largely insulated from the impact of automation- a phenomenon explained through 'Polanyi's Paradox', an assumption that humans possess deep, intuitive, tacit knowledge that makes performing certain tasks quite easy for them but very difficult to teach the same to the machines (Polany, 1966). As these human abilities like interaction and complex language processing were beyond explicit coding, they were also considered safe from algorithmic automation.

However, the theoretical assumptions built around Polanyi's Paradox face a major disruption as GenAI solves this paradox. The capability to infer rules from unstructured data makes LLMs perform high-skill level non-routine cognitive tasks like writing codes, creating creative contents (Eloundou et al., 2023). With this shift in locus of automation from factory floor and clerical tasks to high-skill office works, the traditionally 'skill-premium' tag of cognitive labour requires a re-evaluation.

Wages is a key metric for impact analysis of this shift and there are two competing theoretical frameworks that require examination- the complementarity view that provides an optimistic picture and the substitution view that provides a pessimistic picture.

2.2 Theoretical Frameworks for Wage Determination

Skill Based Technological Change (SBTC) provides an optimistic view of how technology impacts wages. Katz and Murphy (1992) established SBTC as a theoretical framework to understand the relation between technology and wages, which was further expanded by Acemoglu (2002), and SBTC hypothesizes that the positive correlation between technology and productivity is higher among high-skilled workers as compared to the low-skilled workers.

When this 'Productivity Hypothesis' is applied in the context of GenAI, it is found that instead of replacing the workers, these tools automate the routine sub-tasks, thus reducing the marginal cost of cognition. For instance, an AI assistant can make the process of debugging a code must faster for a software engineer (Peng et al., 2023). The standard neo-classical economic theory proposes that in a perfectly competitive market wages are positively correlated with marginal revenue product of labour ($MRP_{L)}$:

$W= MRP_L = MP_L$ X MR
Here the marginal product of labour is represented by MP_L and marginal revenue is represented by MR. Assuming that demand for a specific service is elastic, an AI induced increase in marginal product of labour in terms of increased output per hour will result in willingness to pay higher wages. Thus, this theoretical framework predicts a positive correlation between degree of AI exposure and wage growth as workers get a part of efficiency gained using AI.

However, SBTC has been challenged in the works of Acemoglu and Restrepo (2018). Their modelling of automation using a refined Task-Based Approach reveals two competing forces that emerge:

a) Displacement: Capital (technology) substituting labour to perform certain tasks causes the displacement effect. As the share of automated tasks increases in the daily output of a worker, it results in decreased demand for labour, leading of wage suppression.
b) Reinstatement : Capital (technology) creates new tasks, leading to new employment opportunities. For instance, GenAI may lead to new jobs to perform tasks like prompt engineering, AI ethics compliance and so forth.

What makes GenAI a matter of serious concern is its unprecedented rate of diffusion. The pervasiveness of AI exposure is documented in a report by Goldman Sachs (2023) with over two-thirds of jobs facing varying degrees of AI automation. If the rate of labour displacement is higher than that of reinstatement, it will lead to wage suppression and decline in labour share of income. Service sector industries like basic administrative support that have inelastic demand are likely to experience a lesser number of workers performing the same volume of tasks instead of same number of workers performing higher number of tasks and utility. Within this theoretical framework, AI exposure and wage growth are negatively correlated.

2.3 Skill Levelling Effect

The post-2023 literature diverges from the earlier trends as it explores the distributional aspect of impact of GenAI on skill premiums. Historical trends showed how automation adversely impacted the low-skill workers while aiding the high-skill workers. However, empirical evidence based early trends show an inverse impact of AI.

The impact of GenAI assistant on customer support agents was analyzed by Brynjolfsson, Li, and Raymond (2023) in a landmark field study. With a subject pool of 5,179 agents, this study revealed counter-intuitive results as the least skilled and novice workers gained the most productivity boost (34% to 35%) from AI tools while the experienced or high-skilled workers saw minimal or negligible gains. It was seen as a 'democratization' of expertise as the AI tools captured the 'tacit knowledge' of the best performing agents and made it available to the novices, helping them to perform at the expert level.

This finding creates a paradoxical situation for wage analysis. Within the theoretical framework of SBTC, AI can increase the efficiency of experts, resulting in wider wage inequality between industries like lawyers with AI tools and retail workers without AI tools. On the other hand, the democratizing effect of AI (Brynjolfsson et al., 2023) increases the supply of high-quality performers that can potentially stagnate the wage growth of top earners as the scarcity value of expertise is eroded through commoditization of cognitive skills. This phenomenon has been observed by Noy and Zhang (2023) in their experimental study of professional writing tasks.

2.4 The Methodological Challenge of Measuring 'Exposure'

Any reliable empirical test of these theories is predicated upon a robust metric to measure 'AI Exposure'. Since the GenAI presents a new paradigm of automation, early predictive studies like that of Frey and Osborne (2017) become largely irrelevant due to their focus on robotics and automation of manual tasks.

This limitation of earlier studies into automation are addressed through the development of 'AI Occupational Exposure' (AIOE) score by Felten et al. (2021). They linked specific capabilities of AI ,like image recognition or language modelling , with O*NET job descriptions. Their findings indicated a positive correlation between wages and exposure as high-exposure jobs generally had high wages. However, these findings were from pre-GenAI era.

These methodologies were later updated by the PEW Research Center (2023) and Eloundou et al. (2023) to accommodate the changes brought by Large Language Models. Based on these updated metrices, Information, Finance, and Legal Services ranked as the sectors with highest AI exposure. However, this updated framework still has a major limitation as it only measures the potential exposure, not the actual adoption. While this exposure level indicates the

extent to which AI can perform the tasks, it does not reveal whether AI will be used for worker augmentation resulting in higher wages to worker replacement resulting in lower wages. This paper sees to address this empirical gap.

2.5 Synthesis and Research Gap

An overview of the existing literature clearly establishes the high GenAI exposure level of the US service sector. However, there are contradictory predictions for the economic outcome. While SBTC framework predicts enhanced productivity leading to wage growth, the displacement effect within the Task Based Approach predicts wage suppression, and skill levelling hypothesis predicts wage stagnation for top level workers.

Even more importantly, much of predictive studies (Goldman Sachs, 2023; OpenAI,2023) analyze the task overlap to make potential impact forecast. However, there is very little empirical research into the realized wage data from the early adoption period of 2023-25. This research correlates the AI exposure indices with realized wage growth data (Bureau of Labour Statistics) to find empirical evidence in favour of any of the three effects – Complementarity, Substitution, or Levelling- that currently dominates the US service sector economy.

3. Methodology

This empirical investigation into the impact of AI exposure on US service sector labour market uses a quantitative, correlational research design, based on secondary data. The analysis tests the hypothesized correlation between industry level GenAI exposure and wage variance in the US service sector.

3.1 Data Collection and Operationalization of Variables

For the purpose of empirical validity, this investigation uses the economic construct of 'AI Exposure' as the independent variable and 'Realized Wage Growth' as the dependent variable, both operationalized with precision.

3.1.1 Independent Variable: Quantification of industry level exposure to a General Purpose Technology (GPT) presents significant challenges. While industry exposure to robotic automation as a GPT can be measured in terms of capital investment in machinery, GenAI as a GPT is much complex to track due to its often software-based and decentralized nature. To overcome this methodological challenge, this study uses AI Occupational Exposure (AIOE) index with updated aggregations published by the Pew Research Center (2023) and the Stanford HAI Artificial Intelligence Index (2024).

Definition: The AIOE index offers measurement of degree of overlap between the core tasks of an occupation and capabilities of LLMs. Tasks that can performed or augmented by AI with high accuracy are classified as 'highly exposed' and an industry is given AIOE score based on the percentage share of its workforce employed in jobs with minimum 50% of its tasks being 'highly exposed'.

Justification: The preference for this metric over 'technology spending' data is due to the insight it provides into potential substitution or augmentation of labour based on nature of job. On the other hand, 'technology spending' is an indicator of lagging in corporate procurement.

Data provenance: AIOE scores are linked with the North American Industry Classification System (NAICS) codes to ensure alignment with data from the labour market.

3.1.2 Dependent Variable: Temporal Wage Dynamics measures realized wages or economic value of labour, based on the Current Employment Statistics (CES) survey conducted by the US Bureau of Labour Statistics (BLS).

Metric: Average Hourly Earnings of All Employees is specifically chosen as the metric, over 'weekly earnings', to isolate the economic value of labour from fluctuations in hours worked in week.

Timeframe: This study focusses on the early adoption window, a 24 month period starting from January 2023 to January 2025. As the public release of ChatGPT in November 2022 led to wide-scale adoption of GenAI, January 2023 has been selected to establish the baseline. January 2025 is picked as the end point as it offers a most current validated data point.

Calculation: To address the baseline pay based heterogeneity across industries, for instance the difference in absolute wage in Finance and Retail sectors, the percentage change in nominal wages is taken as the dependent variable (Y):

$$y_i = \left(\frac{W_{i,2025} - W_{i,2023}}{W_{i,2023}} \right) \times 100$$

Where W_i represents the average per hour earning for industry i.

3.2 Sample Selection and Exclusion Criteria

The sample industries (N=10) have been picked from different Supersectors as defined by the BLS.

Inclusion Criteria: The samples are exclusively selected from service industries across Supersectors like Information, Financial Activities, Professional and Business Services, Education and Health Services, and Leisure and Hospitality.

Exclusion Criteria: Supersectors consisting of the Goods-Producing industries have been excluded. Although these industries also use IA, physical capital and manual labour still forms the core of their production activities. Including samples from these sectors would bring associated issues of commodity prices and supply chain as confounding variables that would obscure the specific indicators of cognitive automation- the main focus of this study.

3.3 Statistical Tools for Data Analysis

A selection of standard econometric tools are used for data analysis that provides reliable assessment of strength, direction and predictive accuracy of the relation.

3.3.1 Descriptive Statistics: Before conducting inferential analysis, data screening is used to identify normality and outliers. Central tendency and dispersion for both the variables are calculated using Mean and Standard Deviation.

3.3.2 Pearson Product-Moment Correlation is calculated to test the linearity of the association between both the variables.

- Assumption: It is assumed that the data is interval-level and approximately normally distributed.
- Hypothesis Testing:

$H_0(Null\ Hypothesis): \rho = 0.$ Absence of correlation between AI exposure and wage growth.

$H_a(Aleternative\ Hypothesis): \rho \neq 0.$ Statistically significant correlation.

$Significance\ level\ (\propto) set\ at\ 0.05.$

3.3.3 Ordinary Least Squares Regression: To quantify the 'Algorithmic Premium', a simple linear regression model is constructed. The model specification:

$$Wage\ Growth_i = \beta_0 + \beta_1(AI\ Exposure_i) + \epsilon_i$$

$\beta_0(Intercept)$: It is the baseline wage growth that can be attributed to macroeconomic factors like inflation or shift in labour supply, not AI exposure.

β_1 (Slope): It represents the marginal impact of per unit increase in AI exposure on wage growth.

ϵ_i : It is the error term that represents unexplained variance.

3.4 Methodological Limitations

This study is based on data aggregated at industry level. Hence, the average wages may not represent the individual workers within the specific industry. For instance, senior engineers in the Information sector may drive the wage growth and junior staff may face stagnant wages.

Based on the J-Curve theory of productivity, technological benefits lags behind technological adoption because it requires organizational restructuring that is time-taking process. The narrow time frame may offer only the short term market response and not the long term structural equilibrium.

AI exposure as the independent variable only measures the potential use, not the actual adoption. Policy and regulations may limit the effective adoption, and potentially weaken the observed correlation.

4: RESULTS AND DATA ANALYSIS

Empirical analysis of the data from the Stanford HAI Index (2024), Pew Research Center, and the US Bureau of Labour Statistics is presented in this section.

4.1 Data Tables

The dataset is based on 10 Supersectors in the US economy and wage data presents the seasonally adjusted Average Hourly Earnings of All Employees for January 2023 and January 2025.

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Table 1: Data Aggregation by Industry (N=10)

Industry (BLS Supersector)	AIOE Score (X)[1] (%)	Jan 2023 wage [2] ($)	Jan 2025 Wage[3] ($)	Wage growth (Y_i %)
Finance and Insurance	37.4	43.12	47.38	9.88
Information	36.1	49.82	55.12	10.64
Professional & Technical Services	33.8	47.55	52.26	9.91
Management of Companies	28	52.40	57.11	8.99
Real Estate & Rental	25	34.50	37.40	8.41
Administrative & Support	18	23.50	25.40	8.09
Healthcare & Social Assistance	12	34.60	37.26	7.69
Educational Services	15	31.20	33.54	7.50
Arts, Entertainment & Recreation	9	25.10	26.96	7.41
Accommodation & Food Services	6	19.50	20.87	7.03

[1] Source: Pew Research (2023)/Stanford HAI(2024). [2] Source: BLS CES Jan 2023 (Table B-3). [3] Source: BLS CES Jan 2025 (Table B-3)

Table 2: Summary Statistics

Variable	Mean (μ)	Std. Deviation (σ)
AI Exposure (AIOE)	22.03	11.60
Wage Growth (y_i)	8.56%	1.24%

Based on descriptive analysis, AI exposure shows a broad variance between 6% in Accommodation & Food sector (high-manual service) and 37% in Finance sector (cognitive heavy service), with standard deviation of 11.60. Importantly, nominal wage growth takes place in all the sectors with an average growth of 8.5% and standard deviation of 1.24%.

4.2 **Inferential Statistics**

4.2.1 **Pearson Correlation Coefficient (r)**

$$r = \frac{n\ (\sum XY) - (\sum X)(\sum Y)}{\sqrt{[n\ \sum x^2 - (\sum X)^2][n\ \sum Y^2 - (\sum Y^2 - (\sum Y)^2]}}$$

$$r = \frac{10\ (2009.81) - (220.3)(85.55)}{\sqrt{[10(6063.41) - (220.3)^2][10(745) - (85.55)^2]}}$$

$$r = \frac{20098.1 - 18846.66}{\sqrt{[60634.1 - 48532.09][7457.5 - 7318.8]}}$$

$$r = \frac{1251.44}{\sqrt{12102.01 \times 138.7}} = \frac{1251.44}{1295.6} = 0.966$$

With the value of r being 0.966, AI exposure and wage growth reveals a near perfect linear correlation.

4.2.2 **Significance testing ($p - value$)**

$t - statistic\ is\ calculated\ ¿\ be\ 10.60 \wedge df\ is\ calcualted\ ¿\ be\ 8.$

$p - value: < 0.0001$

This result shows a statistically significant correlation between AI exposure and wage growth.

4.2.3 **Ordinary Least Squares Regression**

$$\hat{Y} = \beta_0 + \beta_1 X$$

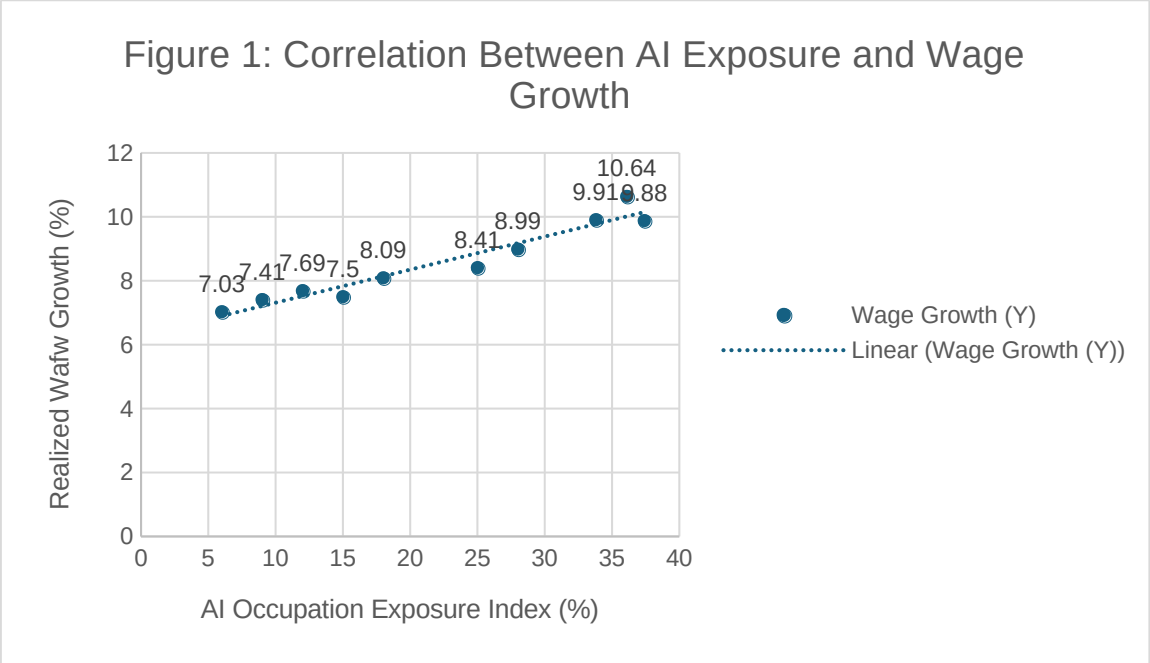
$$Slope\ (\beta_1): \frac{n\sum XY - \sum X\ \sum Y}{n\ \sum X^2 - (\sum X)^2} = \frac{1251.44}{12102.01} = 0.1034$$

$$Intercept\ (\beta_0):\quad Y - \beta_1 X = 8.555 - (0.1034 \times 22.03) = 6.277$$

Final Model:

$$Wage\ Growth = 6.277 + 0.1034\ X$$

As earlier established, there is a highly linear relationship between AIOE and Realized Wage Growth. The below given scatter plot shows this relationship of 10 sampled service sector industries, plotted against the derived regression line.



In the above figure, each BLS supersector is represented by a specific data point. The data points reveals a clear upward trajectory, moving from low exposure to higher exposure sectors. The blue dotted line represents the predictive model $Y = 6.277 + 0.1034\ X$. The high $R^2\ value\ of\ 0.934$ is confirmed by the closeness of data points to this line. Absence of any significant outlier validates the reliability of the model across diverse service sectors with varying level of AIOE.

5: DISCUSSION

Based on the empirical findings of the previous section, there is a positive correlation (r=0.962) between AIOE and realized wage growth across different service sectors. This finding shows that the impact of GenAI based automation on employment diverges from the historical trend.

5.1 AIOE and Wage Growth

The historical trends in automation reveal a positive correlation between exposure level and labour displacement and wage stagnation. However, GenAI based automation reveals a significant divergence from this pattern. Based on the data from 2023-25, exposure level shows a positive correlation between exposure level and wage appreciation. For instance, most exposed sectors like Finance and Insurance, and Information show wage appreciation by 9.88 and 10.64 % respectively.

Based on this finding, the labour displacement impact of automation can be discarded in the context of AI. The positive correlation between AI exposure and wage growth can be indicative of LLMs as cognitive force multiplier. In high AI exposure sectors like finance, AI can automate routine tasks like data synthesis, freeing the human agents to perform high value advisory and strategic tasks. It appears that automation based enhancement in labour productivity is partly transferred to the workers as increased hourly wages.

5.2 Complementarity Effect

The current model being used in this study has high value of $R^2\ (0.934)$, which suggests the primary differentiator effect of AIOE on labour value and two economic mechanisms can provide explanation for this phenomenon:

Skill-Biased Technological change is one explanation. A basic AI literacy (ability of prompt creation, auditing and integration of algorithmic output) is required to use currently available AI tools. In high-exposure sectors, workers with these skills experience increase in marginal product of labour.

Another possible explanation is the talent war for attracting workers with AI-capabilities. With a sudden increase in AI-related job roles in corporates and limited supply of workers with required capabilities, industries with higher exposure have to offer higher wages for attracting and retaining the desired talent.

5.3 Low-exposure Trap

Sectors with low AIOE show a lower wage growth. For instance, sectors like Accommodation & Food Service (AIOE score 6) and Arts & Recreation (AIOE score 9) show lower wage growth of 7.03 and 7.41 % respectively. Although there is wage growth in these sectors, represented by $Intercept\ (\beta_0) = 6.277$ and attributable to inflation and market demand, the AI augmentation induced slope is missing.

It shows the possibility of a new type of digital divide that is based on the potential for task automation. 'Low-Exposure' sectors have majority of tasks that are physical or manual in nature and cannot benefit from the scaling laws of LLMs. Hence, the workers in these sectors are likely to witness a decoupling of wage-growth trajectory from that of sectors with primarily cognitive tasks and high wage growth.

5.4 Productivity J-curve

This research had anticipated a possible delay in benefits of LLMs attributable to Productivity J- Curve. However, the early adoption window between January 2023 to January 2025 already shows a strong positive correlation between AIOE and wage growth. It suggests a much shorter adoption-to-value cycle for GenAI as compared to earlier tools of automation. This phenomenon can be explained by the shorter period of organizational restructuring required for deployment of GenAI tools that are primarily software based and deliverable through existing cloud infrastructure.

5.5 LIMITATIONS

Although there is a very robust correlation between AIOE and wage growth, the long term sustainability of this trend needs further consideration. Investments in AI startups in the Information sector may prioritize speculative over realized productivity, resulting in wage growth that may not be sustainable. Moreover, there may be intra-industry inequality in wage distribution hidden beneath the industry average, as already identified in the methodology section. For instance, in the finance sector the wages of high-level analysists may witness rise but entry-level researchers may experience wage pressure as their core tasks get handled by AI tools.

CONCLUSION

This paper aims to investigate the relation between occupational exposure to Generative AI in different service based industries and wage growth rate. The time-frame chosen for this research is the early adoption window from January 2023 till January 2025. The findings provide empirical evidence that AI exposure is currently a driver and not a deterrent factor for wage growth in the US service sector.

Summary of Findings : Statistical analysis of the findings reveals a significant linear relationship (positive correlation) between AI exposure and realized wage growth. Wage growth rate in sectors with higher AIOE is consistent higher than the sectors with lower AIOE.

Theoretical Implications: The findings of this research support a complementarity model of AI. At its current stage of evolution, LLMs are adding marginal productivity to human cognitive labour, thus making it more valuable rather than reducing its worth.

Policy Recommendation: instead of worrying about the fear of mass unemployment resulting from GenAI based automation, Policy makers should focus on reskilling/upskilling the workers along the transition paths. With a tangible and measurable correlation between AI exposure and wage growth, job loss is not the primary risk associated with AI based automation, it is the widening wage gap between sectors based on level of AI-augmentation.

Further research: Future studies can gather longitudinal data pertaining to firms and individual workers to investigate the impact of AI across different income deciles. Investigations can also look into the threshold of AI exposure turning from a complementary tool of augmentation to that of substitution with the increasing autonomy of AI agents. This methodology can also be used to investigate the labour markets of Europe and Asia or find regional variations.

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