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RESEARCH ARTICLES

Analyzing the Impacts of A.I. on Employment and More in the Primary, Secondary, and Tertiary Sectors

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This study aims to contribute to the ongoing conversation about the current and future impacts of technology on professions and the employment of human labor. The onset of language processing tools from a myriad of companies and the continued digitalization and automation of workloads have led to growing interest in the impacts this could have across the primary, secondary, and tertiary sectors. Some professions face the threat of AI displacement, some have their workload modified, while others remain unimpacted. Measuring and discussing these shifts and changes is a primary goal of this study. This was done qualitatively and quantitatively. Qualitative research of experiences, opinions, and personal insights was first performed to provide a nuanced understanding of possible implications and broad trends. Quantitatively, data from the Bureau of Labor Statistics was then utilized in the construction of linear regression tests to determine whether there are significant relationships between increased AI adoption and employment gain/loss. This research ultimately showed the complex and varying impacts of AI in specific sectors. In the primary sector, statistical analyses reflected a general trend of moderate displacement from AI adoption due to possible compatibility between employees and machines. In the secondary sector, employment is shown to continue to rise despite AI adoption. Generally, AI adoption in that sector is more likely to shift the nature of work instead of replacing laborers. The tertiary sector remains more ambiguous. Because of its large nature and expansive list of industries, understanding the impacts of AI holistically is difficult.

AUTHOR SUMMARY

In the modern day, AI adoption has risen significantly. New technologies are developed each day and their potential use is increasing exponentially. In the context of this, I sought to better understand its implications in the economy and labor force. Analyzing impacts holistically, this paper analyzes the uses and impacts of AI in the primary sector, secondary sector, and tertiary sector. From research and data analysis, we conclude that the impacts of AI differ in each sector but have some underlying similarities. In the primary sector, AI adoption moderately, but not significantly, decreases

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employment. Meanwhile, employment continues to rise in the other sector. This could be caused by a variety of reasons, such as congruence between AI adoption and the nature of an industry's work or a lack of technology. These findings help contribute to the overall understanding of AI's impacts and show how impacts may differ in each sector.

INTRODUCTION

Preface

Since the first industrial revolution, mankind has sought to automate and streamline the world. This was done through new technologies, such as the steam engine, and methods like the steel Bessemer process. What started as simple machinery and novel techniques has evolved to become much more in the present day. Since the "Dot Com" boom of the 1990s and early 2000s, innovation has generated billions of dollars and created entirely new professions and opportunities from digitalization. Now, as countries transition into a time period the World Economic Forum calls the 4th industrial revolution, automation has the potential to reach new heights of sophistication and utility with the onset of artificial intelligence (Schwab, 2016). From search engine extensions to graphic editors, AI has the potential to impact nearly every sector of the economy. The extant research is limited when examining the implications of AI in specific economic sectors. Therefore, this paper investigates automation in primary, secondary, and tertiary sectors, with an emphasis on changing employment trends.

Definitions

For the purpose of this paper, economic sectors will be divided into primary, secondary, and tertiary sectors to provide a more holistic view that considers broader context and interconnection. The primary sector refers to industries involved in the extraction and production of raw goods (Insee, 2020). This includes industries such as agriculture, mining, forestry, fishing, and other industries that produce raw materials. The secondary sector consists of industries that utilize raw materials to create goods and finished products, such as the manufacturing and construction industries (Insee, 2020). The tertiary sector refers to industries that offer an intangible service to businesses and consumers (Insee, 2019). This is the broadest economic sector, including professions that sell retail goods manufactured in the secondary industry to those that supply knowledge and expertise, such as in medicine or law.

Automation refers to the technique, method, or system of operating or controlling a process by highly self-operating means, such as electronic devices, reducing human intervention to a minimum (Visser & Obi, 2019). This paper focuses on automation from artificial intelligence and robotics. Artificial intelligence, or AI, will be defined using the OECD's (Organization for Economic Co-operation and Development) definition of "a machine-based system that is capable of influencing the environment by producing

an output (predictions, recommendations, or decisions) from a given set of objectives." A wide range of intelligence levels will be included, such as human-controlled robotics and generative pre-training transformers (GPTs) like Chat-GPT and Bard.

Literature Review

Many papers have already studied and attempted to measure the impacts of AI on the economy based on tasks and professions. These studies may differ in opinion, but they often have similar conclusions or takeaways. For example, many agree that those who perform tasks that are routine are at greater risk of displacement. There is also job polarization that often occurs between highly skilled labor and unskilled labor, with those in professions between these two sides of the spectrum being most impacted by automation. Studies have also been done on Language Learning Models (LLMs) such as GPT-4. Eloundou et al. (2023) apply a novel rubric on data to measure levels of "exposure" (economic impact from either labor change or displacement) certain jobs have to AI, finding that approximately 19% of jobs have at least 50% of tasks exposed to LLMs. This paper aims to contribute to the ongoing literature by taking a more holistic look at the impacts of automation and AI through the lens of the three-sector theory instead of individual professions. In doing so, it hopes to reveal expansive trends and distinctions within and between sectors, revealing interdependencies and potential consequences from intersectoral relationships.

Methods

This paper utilized a two-pronged analysis: first qualitative, then quantitative. The impacts of AI were first understood through the corroboration of various academic papers in order to reach broad conclusions. Large databases like Google Scholar were searched using keywords related to specific sectors, and specific sources were selected depending on the relevance of the information to either AI implementation or AI impact on employment. After determining broad trends, quantitative analysis was done to substantiate the data. Using the employment and wages data viewer from the Bureau of Labor Statistics, data on industries outlined by the North American Industry Classification System (NAICS) were found and utilized in multiple linear regression tests for each sector. The dependent variable for all tests was the employment figures of the custom computer programming services industry. This classification includes services like industrial robot programming, computer programming, and machine vision software design, a clear representation of AI implementation. The independent variables were the employment figures of specific industries and sector aggregates found by adding up employment in all industries within a sector, as defined previously in the definitions. A significance level of $\alpha = 0.10$ was used for all significance tests. Using this process, graphs on

aggregate employment and those on employment within specific industries were constructed, except for the tertiary sector. Due to its expansive list of industries, only an aggregate linear regression was constructed.

Overview/Context

The use of automation and the development of AI has increased substantially over the past ten years. Algorithms and machine learning have become ubiquitous across the Internet. YouTube supplies its audience with media based on consumption patterns, Facebook advertisements target consumers based on searches and browsing patterns, and Spotify recommends music based on preferences. More recently, research and development have shifted to focus on the creation of neural networks, algorithms that learn and adapt to fit additional data. OpenAI launched DALL-E and Chat-GPT (the former develops images based on text descriptions while the latter responds to prompts as a language model). Meanwhile, other companies have launched accessories for products like Google's search engine add-on Bard, which aids the searching process by giving clear, direct answers. OrganAdobe is an add-on for Photoshop's Generative Fill, which allows its users to edit images simply with prompts. This is a stark contrast from the mid-2010s, as McElheran et al. (2022) found that a mere 2.9 percent of firms used machine learning in 2017, while Acemoglu et al. (2022) report only 3.2 percent used AI as part of their processes between 2016-2018. Within these percentages, larger firms in industries that provide services have been most likely to adopt AI (The White House, 2022). Since these advancements, AI adoption has increased substantially, with 25% of companies using AI and 43% exploring potential future applications (IBM Corporation, 2022). Additionally, the adoption of AI for personal use has increased substantially. In 2019, the percentage of Americans using a digital voice assistant such as Alexa, Siri, or Google grew to 72 percent (Olsen & Kemery, 2019). With the onset of recent models, the market size of AI is expected to reach $407 billion by 2027, increasing at a compound annual growth rate (CAGR) of 37.3 percent from 2023 to 2030. With AI's substantial and extensive growth, analyzing its broad impacts becomes crucial to comprehending its influence.

PRIMARY SECTOR

Current AI applications

Artificial intelligence in the primary sector, while yet to be thoroughly implemented across industries, has been utilized in specific applications. When implemented, AI has been primarily used in analysis with information systems while only sometimes being deployed in physical machinery and labor, depending on the environment. In forestry, there is an absence of fully autonomous systems and machinery because of a lack of larger-scale market demand for harvesting machinery and a less homogenous environment compared to other primary industries like agriculture and mining (Visser &

Francis, 2020; Holzinger et al., 2022). Despite this, AI information systems have made mapping and planning more efficient with the use of sensors, satellite technology, geographic information systems, and other information technologies (Holzinger et al., 2022). The mining and agriculture sectors exhibit comparable trends, yet they also feature unique variations due to the distinct nature of their operations. As Hyder et al. (2019) stated, applications of AI and autonomous technologies in mining are still in their infancy but have actively been implemented over time. These applications can be seen in a variety of areas from data analysis in prospecting and exploration to even the use in fleets of autonomous vehicles because of private roads owned by corporations. Moreover, agriculture, like mining, has had various uses of AI systems and algorithms in information systems but lacks much implementation in physical equipment. AI is already being used for a variety of tasks like general crop management, pest and disease management, product monitoring and storage control, soil and irrigation management, weed control, and yield prediction (Ghosh et al., 2018). However, most AI robotics and physical equipment in agriculture are still in development and only just reaching commercial sale (Shamshiri et al. 2018; Shutske. 2022). Overall AI is still being adapted, and a clear trend of increased adoption is visible. Indeed, data adapted from employment projections of software developers show an estimated 25.5% and 13.9% increase in software developer employment within agriculture/forestry and mining, respectively. As technology improves, AI's uses within these industries will only continue to grow.

Impacts on the Sector and Employment

Artificial intelligence has a variety of impacts across primary industries. Because of the primary sector's focus on raw materials, the most obvious and prevalent effect is greater efficiency and productivity through streamlined processes that could otherwise take much longer, allowing for greater yields of resources (Visser & Francis, 2020; Hyder et al., 2019; Wang & Wang, 2022). AI also increases efficiency by presenting solutions to existing problems, subsequently helping humans make better decisions. This is most noticeable in agriculture, which uses AI to solve a variety of problems like the presence of disease and pests that would impact the yield of crops. In contrast to these positive benefits, Ryan (2022) notes that a negative consequence is the chance of an expanded digital divide; AI may often only be deployed in larger farms that could afford the integration, leaving poorer, smaller farms deprived of these beneficial technologies.

For employees in the primary sector, AI may be beneficial. Rather than replacing workers, it may allow for safer, less strenuous working conditions in industries that are highly laborious. For instance, mining—which is dangerous and hazardous by nature—can become safer with equipment that autonomously monitors air quality, locates hazardous areas, and sends warnings and signals (Hyder et al., 2019). Advancements in technology have already steadily decreased the fatality rate in mining from an average of

30.15 deaths in 2000 to 11.77 deaths in 2022 (The National Institute for Occupational Safety and Health [NIOSH], n.d.). The same can be said for forestry and agriculture, which each have similar uses for AI (Carolan 2020).

However, with AI performing tasks that are crucial to operations, job loss is understandably a major concern among employers and employees. In interviews with experienced mining employees, Hyder et al. (2019) note that 90% thought AI would have a negative impact on employment opportunities in mining. This may lead to resistance from workers and supervisors, which has been cited as a leading challenge in AI adoption. The current state of advancements may suggest that AI could better complement workers in the primary sector as opposed to replacing them. In agriculture, for example, Marinoudi et al. (2019) indicate robust alignment and complementarity in the integration of AI, indicating the mutualistic relationship between machines and humans. Meanwhile, interviewees from large agribusinesses say human agronomists will not be replaced by AI anytime soon (Ryan, 2019). This congruence creates a need for skilled employees. Indeed, interviews from Hyder et al. (2019) state that lack of expertise and skilled labor force is the most common challenge in implementing these technologies in mining. Carolan (2020) emphasizes that the skillset for utilizing new robots in farming may be limited to educated, skilled individuals. Overall, it is clear that job displacement effects are often not as negative as they seem at face value.

Data Analysis

Linear regression tests done on the aggregate employment in the primary sector, as well as the industries within, produced results in agreement with the conclusions stated above. The regression model placed on aggregate employment and custom programmers produced a p-value of 0.105, which is insignificant at $\alpha = 0.10$, leading to the conclusion that there is not convincing evidence of a statistically significant negative, linear relationship between custom computer programming services and employment in the primary sector. Despite this conclusion, a correlation coefficient value of -0.285 reveals a moderate, negative relationship between the two variables, which can be seen in Figure 1. Performing the regression test on industries within the primary sector yielded similar results. The test was conducted on agriculture, forestry, fishing, and hunting, generating a p-value of 0.316 while also showing a negative trend line. In contrast to these previous results, analysis done on natural resources and mining gave a p-value of 0.058, making it statistically significant at $\alpha = 0.10$. This means there is convincing evidence of a negative, linear relationship between employment in natural resources and mining and employment in custom computer programming. These marginally significant results help further illustrate that AI, while potentially already impacting employment, hasn't yet had a remarkable influence.

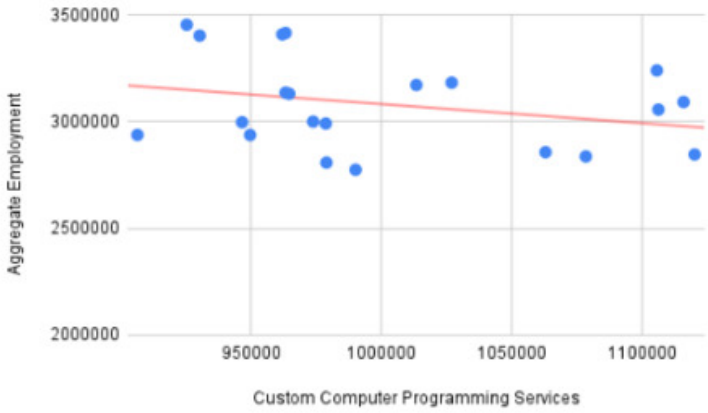

Figure 1. *Relationship between Primary Aggregate Employment and Custom Computer Programming Services Employment.* Data Adapted from BLS Quarterly Census of Employment and Wages.

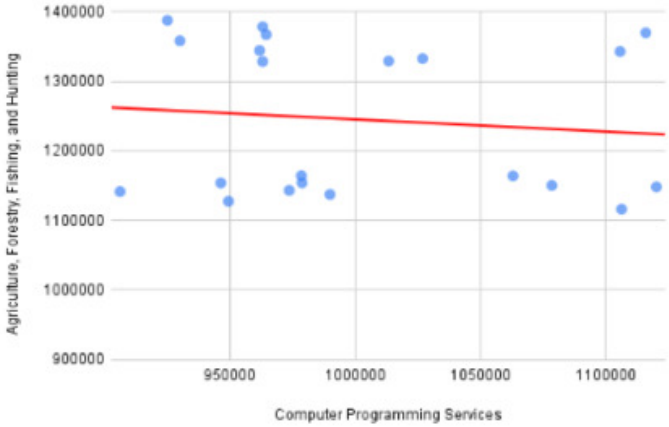

Figure 2. *Relationship between Employment in Agriculture, Forestry, Fishing, and Hunting and Employment in Custom Computer Programming Services.* Data Adapted from BLS Quarterly Census of Employment and Wages.

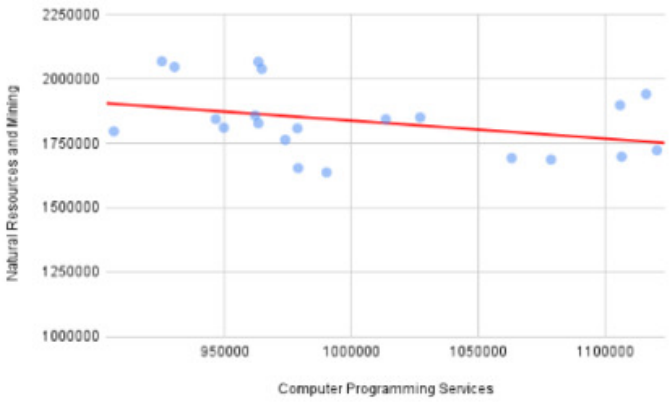

Figure 3. *Relationship between Employment in Natural Resources and Mining and Custom Computer Programming Services.* Data Adapted from BLS Quarterly Census of Employment and Wages.

SECONDARY SECTOR

AI Applications

AI is utilized for two primary purposes in the secondary industry: planning and logistics, and physical creation. AI aids in completing a variety of tasks that come before the creation of a final product. For example, AI optimizes design and materials. In manufacturing, algorithms can generate designs based on prompts and details, exploring numerous configurations until the optimal one is found (Buchmeister & Palcic, 2017). Similarly, construction deploys AI to optimize waste and material use in processes from offsite construction to material selection (Regona et al., 2022). In addition to optimization, AI provides predictive analytics from sensor data, which are employed in maintenance, supply chain management, and other applications (Buchmeister et al., 2019; Regona et al., 2022). In manufacturing, computer vision using AI helps detect defects or anomalies and helps machines execute assembly stages that help create the finished product (Arinez et al., 2020; Buchmeister et al., 2019). Meanwhile, AI-powered equipment automates traditional physical tasks such as bricklaying or paving roads on construction sites (Chui & Mischke, 2019).

Impacts on the Sector and Employment

Corresponding to the primary sector, the effects of AI on the secondary sector are diverse but generally centered around output. In both manufacturing and construction, utilization of AI and machinery means lower overhead and greater efficiency from the use of AI-powered machinery (Akinradewo et al., 2021; Buchmeister et al., 2019). Buchmeister et al. (2019) also assert shifts in aspects of work for manufacturing. This includes increased process improvement, innovation testing, and custom products, while also decreasing costs related to machine repair, issue resolution, and standard products.

The implementation of AI in the secondary sector will dramatically shift employment dynamics. The largest impact will be on the skill level of those employed. In manufacturing, Buchmeister et al. (2019) find that AI will force humans to shift from roles that perform repetitive tasks to more complex and innovative ones. In construction alone, 38-45% of its jobs could be completed by AI analytics or robotics in 2030 (Regona et al., 2022). Although some basic roles will inevitably be replaced, AI is more likely to change the performance of tasks in manufacturing and construction than completely replace them (Buchmeister et al., 2019). As Chui and Mischke (2019) state, it's improbable that a construction company will terminate a carpenter's employment and replace them entirely with the newest robot. Instead, machines will assume specific tasks within a job. This implies that employees will have to adapt to working alongside machines or in a combined role with them. Additionally, the implementation of AI could create new positions that previously would not have existed, such as AI engineers, technicians, and trainers (Regona et al., 2022). Because of these reasons,

employment in these industries is still expected to grow. In construction alone, jobs are predicted to grow by an additional 200 million worldwide (Chui & Mischke, 2019).

Data Analysis

Linear regression models done on the aggregate and in each industry all show obvious positive trend lines. Because of this, all tests were done with the alternative hypothesis of $\beta > 0$. For aggregate employment (shown in Figure 5), the linear regression model gave a p-value of 0.007 and a correlation coefficient of 0.527, giving statistically convincing evidence of a positive, linear relationship between aggregate employment in the secondary sector and computer programming services. Tests done on individual industries gave similar results. In manufacturing, a p-value of 0.111 fails to make the relationship significant; however, as Figure 5 shows, a positive trend is still viewable. Correlation in construction is clearer; a p-value of 0.0001 provides definitive evidence of a positive, linear relationship between construction employment and programming services.

TERTIARY SECTOR

AI Applications

AI applications are more complex in the service sector because of the added levels of social intelligence and analysis needed for most service jobs. It also encompasses many more industries than the primary and secondary sectors, many of which are outside of the scope of this paper. For the purpose of analyzing AI implementation, the sector will be split between services for people and services for businesses. There have been a variety of applications for consumers. Voice assistants like Alexa and Google have become ubiquitous in the modern age, helping users with various tasks from ordering products to sharing the weather forecast. Stores like Amazon Go have ditched cashiers for AI-powered cameras and sensors. More recently, the rise of generative AI models has given the public access to a new wave of innovative AI technology with endless applications. OpenAI's "ChatGPT," an AI that answers prompts from the user, has already been used by millions across the globe for everything from recipe ideas to being a math tutor at Khan Academy. DALL-E, a neural network that creates images based on prompts, gives anyone the ability to create complex art from their imagination. For businesses, AI has become a powerful tool in even the most complicated tasks. Algorithms dictate user content on some of the world's most popular websites like Amazon and YouTube (Huang et al., 2019). IBM's AI, "Watson," has been helping businesses analyze and interpret data for years, even helping H&R Block prepare taxes (Huang et al., 2020). In medicine, AI algorithms can analyze patient data to diagnose diseases more accurately and quickly than their human counterparts, though this application is still in its infancy (Al-Antari, 2023). These examples are just a glimpse of the expansive list of utilizations.

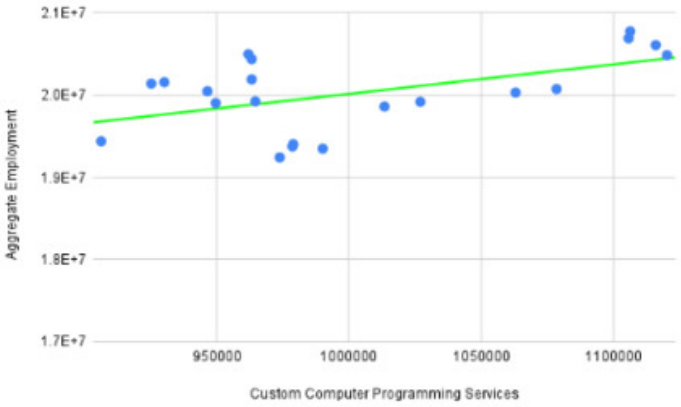

Figure 4. *Relationship between Secondary Aggregate Employment and Custom Computer Programming Services.* Data Adapted from BLS Quarterly Census of Employment and Wages.

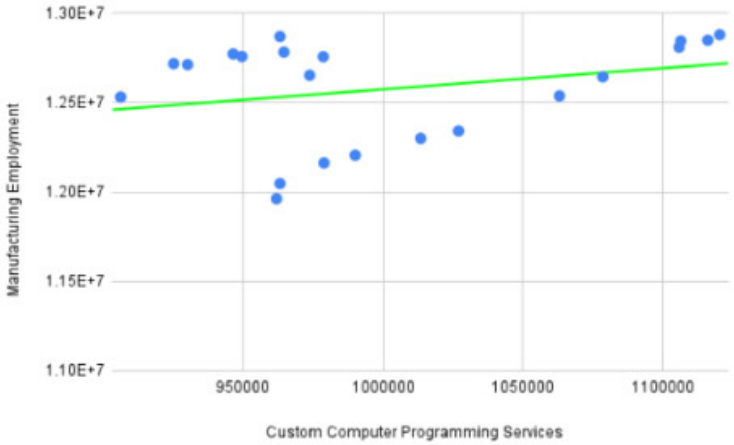

Figure 5. *Relationship between Employment in Manufacturing and Custom Computer Programming Services.* Data Adapted from BLS Quarterly Census of Employment and Wages.



Figure 6. *Relationship between Employment in Construction and Custom Computer Programming Services.* Data Adapted from BLS Quarterly Census of Employment and Wages.

Impacts on the Sector and Employment

As mentioned earlier, the tertiary sector encompasses many more industries and professions than the previous two sectors. As a result, the impact of AI may differ depending on the industry; however, broad trends can still be established across the sector as a whole. Overall, the implementation of AI underscores the need for skilled labor, primarily, followed by the distinctive "soft skills" that technology in the tertiary sector currently lacks in comparison to humans (Huang et al., 2020). For example, restaurants may decide to maintain human servers in order to maximize customer service. This dynamic produces strong job polarization. Well-paid skilled jobs that require non-routine cognitive skills experience increased demand, middle-paid jobs that typically require routine manual and cognitive skills drop in demand, and low-paid, low-skilled jobs that require non-routine manual skills increase (Petropoulos, 2018). This polarization is emphasized in a sector that has an abundance and large variety of jobs. But as Zarifhonarvar (2023) notes, the effects of generative AI on the job market are difficult to predict and can have outcomes. One positive possibility is that AI could increase job opportunities and wages by increasing productivity. This subsequently would lead to greater economic growth and labor demand.

Data Analysis

Unlike the prior two sectors, data analysis on the tertiary sector could only be done in the aggregate because of the abundance of industries. The resulting linear regression model gave a p-value of .013 when tested with the alternative hypothesis > 0, illustrating a statistically significant positive, linear relationship between increased software development professions and employment in the tertiary sector.

DISCUSSION

This paper sought to understand the past and current impacts of AI on employment and production within economic sectors. The results show the varying extent of AI impacts in each sector, backed by potential causes of these results. In the primary sector, p-values close to significance and negative trends support the idea of moderate job displacement. As outlined in the impacts section, AI better supports workers in primary industries than outright replacing them, a sentiment reflected in the moderate correlation between the two employment variables. Ultimately, the current adoption of AI in industries like farming or mining improves conditions and labor for employees rather than displacing them. Statistical analysis done on the secondary sector also reflects conclusions reached prior to analysis. As asserted, manufacturing and construction employment is still expected to increase despite AI adoption and automation, a clear trend shared by figures five, six, and seven as well. From these aligned conclusions, it can reasonably be inferred such trends could in part be caused by the conjectured trends of both altered work instead of replaced work and new professions from AI in

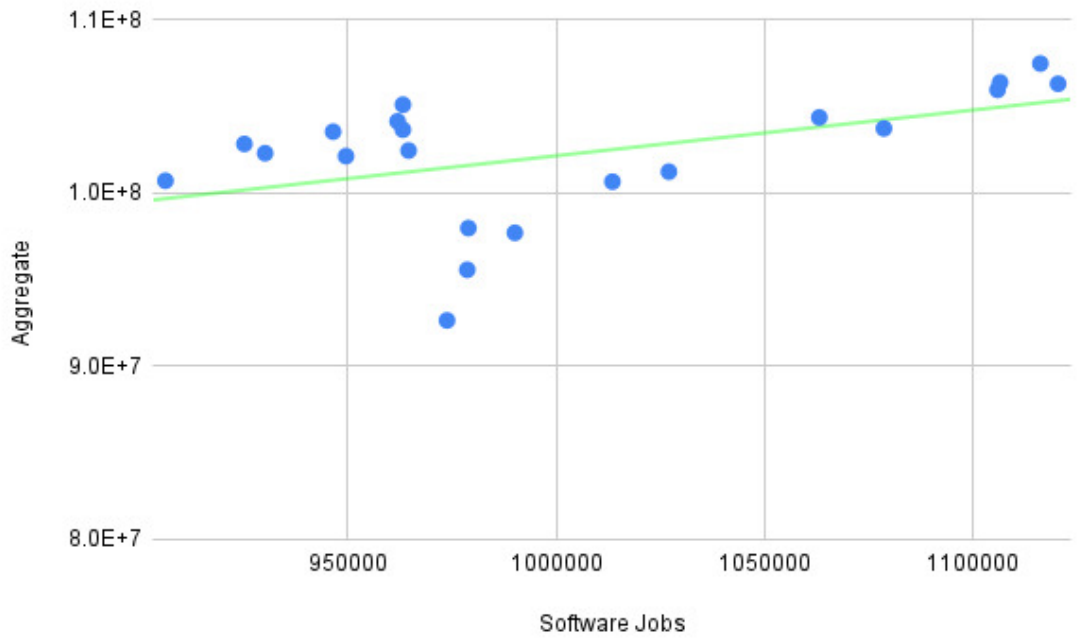

Figure 7. *Relationship between Tertiary Aggregate and Custom Computer Programming Services.* Data Adapted from BLS Quarterly Census of Employment and Wages.

these industries. However, it is important to note that the correlation could be caused by other external factors as well. In manufacturing specifically, general industry expansion or political impacts like policy supporting domestic manufacturing could also influence overall employment. In the tertiary sector, results are more inconclusive. While there is a statistically significant positive relationship, it is difficult to measure the relationship between AI adoption from software development employment and overall employment since those software professions are within the tertiary sector itself. In all sectors, a few general trends are clear. One universal movement is a shift towards skilled labor. As artificial intelligence continues to improve, skilled positions will become more and more necessary; whether it's engineers or software developers, increased use of AI in any sector will mean an increased need for labor that supports these structures. And as a result of this shift, there is an increasingly wide polarization between non-routine unskilled labor and these new skilled professions. These findings help shed light on a topic that will no doubt continue to have profound impacts on the labor market. However, there are still many avenues that require further research and understanding. Because of the chosen structure of analysis, the tertiary sector remained largely obscure. Further study can be done on the tertiary sector alone because of its vast number of industries that have a large range of skill levels and routines. Additionally, a better understanding of the other implications of AI advancement needs to be achieved. Aspects like wages and the actual experience of these new work environments need

further elaboration. In the future, hopefully these conclusions are able to help inform policymakers, employers, and individuals seeking to navigate the evolving landscape of work and employment across the three-sector model.

For a comprehensive summary of Slope Coefficients and P-values, please click this link.

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