HUMAN MACHINE COHABITATION

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COHABITATION OR REPLACEMENT

The COVID-19 pandemic accelerated the pace at which businesses began to automate their production facilities. Necessitated by the unavailability of in-person workers and promoted by new advances in technology, automation found footholds in businesses that it had never successfully infiltrated before such as meatpacking (Lynch 2021). However, not every industry was impacted equally by the pandemic, software development does not require onsite laborers or specialized equipment. Despite not having to make any changes in order to work remotely software development began to rapidly automate as well. The best example of the rapid growth of automation in the software development industry is low code development which increased 23% to a market total of $13.8 billion in the course of a year (Gartner 2021). Despite the pandemic, automation, and the fact that there are 17.6 million fewer available jobs, tech occupations grew by 1.2% over the course of a year according to the Bureau of Labor Statistics (U.S. Bureau of Labor Statistics 2022). The case study of how low-code development platforms impact the software development industry can be used as a stepping stone into a broader question of why and how automation has traditionally negatively impacted other industries and an inquiry into what can be done to mitigate the harm done by automation.

Low-skill laborers fear complete displacement by machines according to research done by Johannessen (2019). The job insecurity that already existed was exasperated by the COVID-19 pandemic which caused thousands of laborers to lose their jobs and led to a 16.7% increase in automation (Lynch 2021). As the world transitions out of a global shutdown, the question becomes will the jobs of these displaced laborers still exist are they now performed by a machine? The workers' fears are justified, over time there has been a dramatic shift in the rate at which jobs are created and the rate at which workers are displaced. Dizikes (2020) found that between 1947 and 1987 jobs were displaced at a rate of 17% and created at a rate of 19%. Disturbingly, in recent years this has changed with the rate at which jobs are generated falling to 10% and the rate at which workers were displaced rising to 16% between 1987 and 2016 (Dizikes 2020). These rates likely increased significantly in recent years with 17.6 million jobs disappearing over the course of the pandemic (U.S. Bureau of Labor Statistics 2022). This research paper attempts to couple the technical overview of how automation impacted software development with the social construction of technology framework analysis of the broader trends of automation in order to answer the question of why automation differs so much between industries and what dangers it presents, as well as how these dangers can be mitigated. To do so the paper will first address what are the typical problems that occur when automating labor, then perform a social construction of technology analysis of automated technologies to gain a better understanding of why these dangers occur, and finally, propose how restructuring the development process of automated technologies could shift the relevant stakeholders in a manner which allows the technology to lessen the harm done by automation.

THE COST OF AUTOMATION

Automation can impact laborers and society in many different ways, some of which are more apparent than others. Displacing laborers, causing wages to lower, creating job shortages, and overworking employees are all easily identifiable ways in which automation harms workers. Other dangers of automation such as bias in algorithms, the misattribution of blame to laborers, and displacement that goes unnoticed due to the value placed on laborers are harder to detect and take mitigating action against.

THE VISIBLE IMPACTS OF AUTOMATION

It matters why we automate; Estlund (2021) shows that businesses automate production facilities because machines require less than humans, you do not have to pay their salary, their pension, or their healthcare. It is also important to understand the nature of automation, too often automation is thought of us as the displacement of individual laborers by an individual machine. However, automation comes about as a tool that allows an individual laborer to increase productivity. Productivity, as defined by Lynch (2021), is the amount of product generated by a singular laborer in a unit of time, and this metric has gone up in spite of the pandemic. With fewer people available to work, more investment in equipment and tools occurred, allowing the remaining workers to meet the same productivity goals (Lynch 2021). This was confirmed by The Government Accountability Office (2019) which found that businesses that automated aspects of labor required fewer workers to reach their production goals. However, once these goals were met with fewer employees, businesses would have to make a decision about whether they would redistribute their employees or simply lay them off (Office U.S.G.A, 2019). This data was drawn from an analysis of how low-skill workers are impacted by automation and these trends are not guaranteed to apply to the automation of high-skill labor.

Automation is normally thought of as displacing low-skill workers by supplementing them with machines, yet there is a similar degree of automation in complex labor and even managerial positions (Acemoglu & Restrepo 2017). It is no longer only the factory worker who need to fear losing their job in response to a new robot being installed; managers and white-collar laborers are now similarly at risk of having to compete with a new algorithm or robot. As the displacement of high-skill laborers, such as those with a 4-year university degree, increases, low-skill and often less-educated laborers must now compete with these candidates. Additionally, the automation of managerial networks has been shown to negatively impact worker-manager relationships. The prevalence of these managerial networks in gig work such as delivery drivers, another form of labor on the rise due to the pandemic, has left workers highly exploitable (Jarrahi et al. 2021). Jarrahi and their fellow researchers (2021) found that managerial networks, used for distributing workers and assigning orders, often lead to overworking employees and distributing them in ways that prioritize profit over the wellness of the workers.

THE INVISIBLE IMPACTS OF AUTOMATION

Less apparent in the previous example of managerial networks is how the algorithm of the managerial network can impact who receives their orders in a timely fashion (Jarrahi et al. 2021). This is an example of the unseen cost of automation which occurs in the form of algorithmic biases. Systems that are automated tend to have a bias towards or against certain types of interaction (Fereidunian & co. 2007). It is pointed out by Fleischmann & Wallace (2006) that bias within automated systems is correlated with the ethical frameworks of the people who designed the system, these biases then shape how the machine or algorithm interacts with humans. This human element in the bias of automated systems has been shown to be nearly impossible to prevent and must be accounted for when discussing the cost of automation, such as with the functionality of micro-systems (Tubaro & co. 2020). The potential harm caused by algorithmic biases can also be highly specific such as examining the race of an individual when attempting to purchase a home or inspecting the health conditions of a potential employee during the hiring process. While these same biases exist in humans, humans are capable of recognizing this and adjusting for it in a way algorithms are not.

Other unintuitive problems with automation arise not from algorithmic biases, but from human ones that appear oftentimes to be artificially constructed. Scroggins and Pasquetto (2020) point out that often times we fail to take note of the impact of automation because it is replacing invisible labor, which society fails to attribute value to. Invisible labor is often unacknowledged and goes unrewarded, and as a result when these positions become automated people are unlikely to notice. Labor such as data management, where number crunching was once done by hand, is now being handed off more and more frequently to algorithms that can perform it faster and more efficiently at the cost of only a few laborers' employment (Scroggins and Pasquetto 2020).

Other times our bias prevents us from attributing blame to automated systems Elish (2019) describes the moral crumple zone as the use of human actors as scapegoats for the systems. When an individual crashes a self-driving car they are blamed because they were behind the wheel, when the Three Mile Island reactor overheated the blame was heaped on the shoulders of the workers involved (Elish 2019). Elish’s view becomes particularly poignant in light of the journalism done by Siddiqui and Albergotti (2022), who analyze the danger of Tesla’s self-driving cars. The invisible cost of automation in some cases is both the workers who are being held liable for improperly designed systems as well as the workers who are displaced.

WHAT MAKES SOFTWARE DEVELOPMENT DIFFERENT

Software development was an industry uniquely predisposed to flourishing during a pandemic. Restaurants cannot operate without workers in person, but developers could do the same labor from any location so long as they had a laptop. Coupled with a growing need for developers as more businesses were forced to transition online it is easy to see where the increased demand for developers came from and why the industry grew while most others languished. Figure 1 below gives a visual indication of the degree to which software

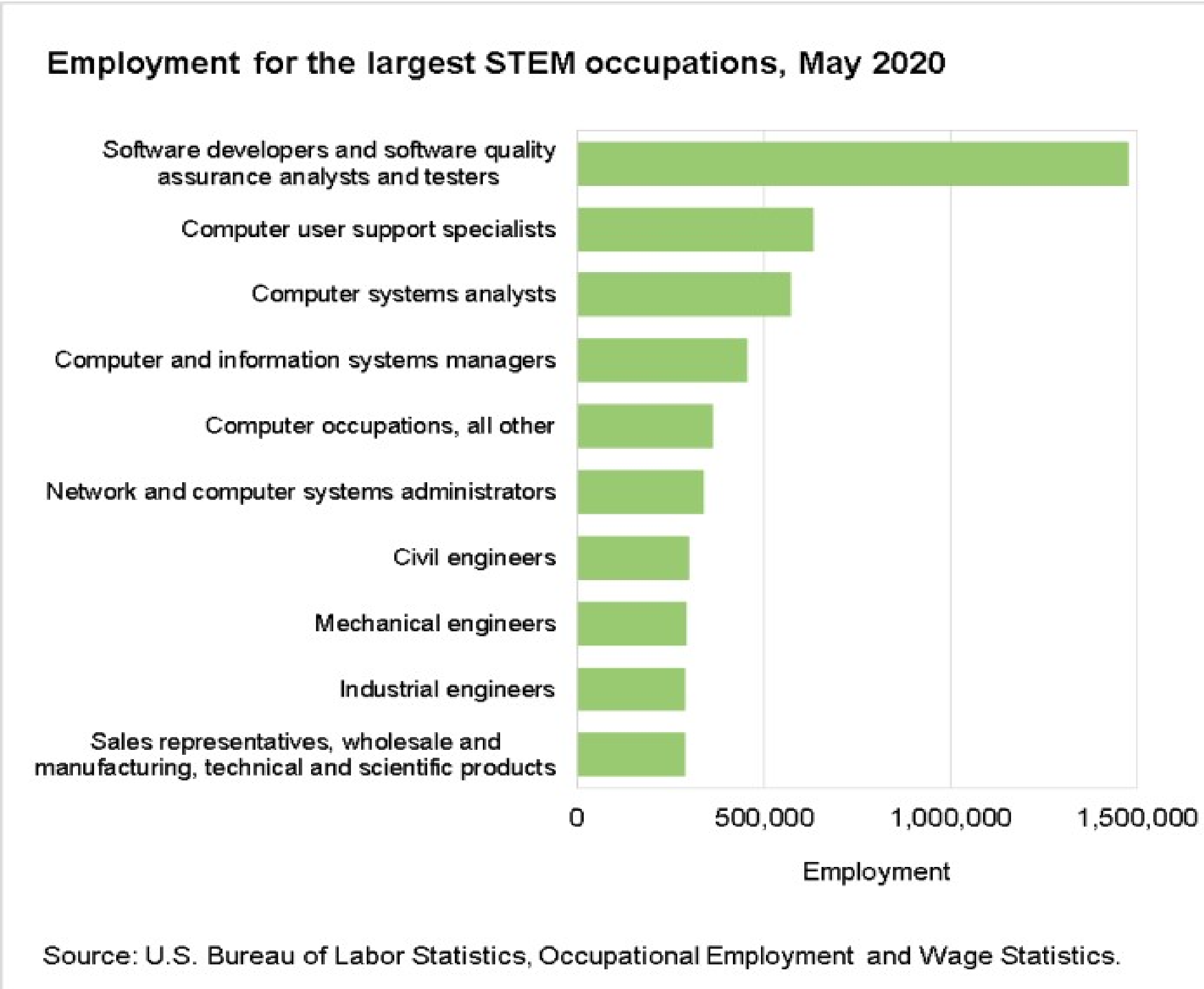

Figure 1: Employment for largest STEM occupations. The figure shows the data collected by the U.S. Bureau of Labor Statistics on the number of employees in various STEM based occupations. (U.S. Bureau of Labor Statistics 2022).

development is still outpacing other STEM industries in terms of size. However, this does not imply that software development uniquely handled automation or explain why automation has failed to have any negative impact on the employment of developers. One can argue that it is simply a need-based issue, that the demand for software developers is still increasing at a greater rate than workers are being displaced. But that seems improbable based on the growth rate of low-code developments and the increases in productivity it offers. Pichidtienthum et al. (2021)

through careful analysis of the Odoo platform, demonstrated that low-code development platforms lead to an over 20% increase in productivity among developers. This information coupled with the 23 percent market share growth found by Gartner (2021) that low-code development platforms have experienced in the past year, seems sufficient to demonstrate that automation is increasing productivity without displacing laborers.

Importantly, while low-code development was the primary focus of the technical research it is not the only form of automation occurring within the software development industry. Recent improvements in the automation of software testing allow for a form of labor to be nearly completely replaced. Software testing is the practice of thoroughly testing each component of the software, it can be performed manually and is often used in small instances to ensure the program is functional. More recently, software testing frameworks have been developed to generate a software testing suite that effectively tests any given software (Winkler & co. 2010). This means that not only are laborers not required to manually input test cases anymore, but the technology has progressed beyond the point of requiring laborers to design automated testing frameworks, now there are algorithms that completely handle the process. This means that an essential role of any software development team has been removed. Testing was often a quarter or more of the work involved in the development, yet developers are still being hired as quickly as they can get degrees. It is not a unique position held by the software industry that allows employees to avoid bearing the cost of automation but rather a difference in how the automation is designed. Their position is only unique in that software developers perform the automation of their own labor.

SCOT ANALYSIS OF AUTOMATION

Social Construction of Technology is based on the idea that human action determines the course of technology more than technology shapes human action (Klein & Kleinman, 2002). A SCOT analysis of technology involves looking at how the relevant stakeholders and social groups shape the development of that technology. In the case of automation, there are several relevant stakeholders with different influences on the design of the technology. These include but are not limited to, the corporation that wish to automate labor, investors who own capital with the corporation, the workers who fear displacement, the engineers who design the technology, the consumers who use the products produced, and the government whose job it is to regulate the businesses. Software development finds itself uniquely situated as an industry by having many of the stakeholder groups overlap.

Corporations want automated software that improves productivity, but in the case of software engineering, the developers are often both the engineer designing the technology and the worker who fears displacement. Software developers are aware of their own needs, what kind of tools would be most beneficial to improving their productivity, as well as what kind of tasks would be easiest to automate. Because of this, they mitigate the danger to their own profession by designing tools of automation that allow for the greatest productivity while not eliminating their own necessity. Certain roles, such as software tester, may soon be a thing of the past, but this only results in a redistribution of an employee rather than the removal of one. This demonstrates the concept that by having the engineers and workers be closely related they can oftentimes produce a form of automation that is more conducive to human-machine cohabitation.

A reframing of automation based on the potential shown in software engineering could go a long way in protecting the jobs of both low and high-skill laborers. Figure 2 represents how automated technologies are presently developed in a SCOT view. By using their capital businesses can increase their production by developing new technologies. The technology

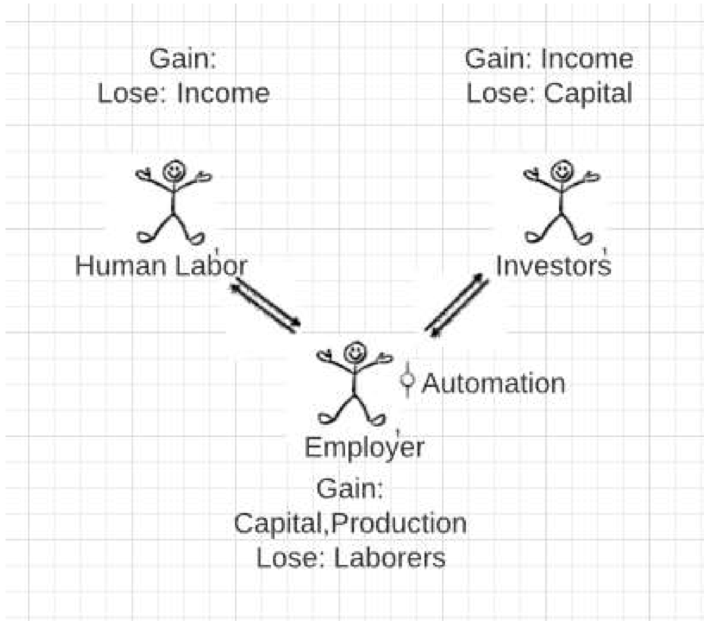

Figure 2:Technology and Social Relationship Model for Automation. The technology and social relationship model demonstrates how automative are designed to displace laborers. In this model it can be seen that the laborers are excluded from the process and eventually replaced by the technology in order to generate profit at a lower cost. (Bremer 2021)

is developed by engineers but independent of the laborer and with the intention of replacing them. From this model, the stakeholder groups such as engineers, investors, and engineers benefit greatly because the same productivity occurs but the cost of labor has significantly decreased since the employer no longer has to pay wages. However, this model adversely impacts workers as a social group causing either a reduction in wages or complete displacement from work.

In software development, the model looks more similar to Figure 3 below in which the

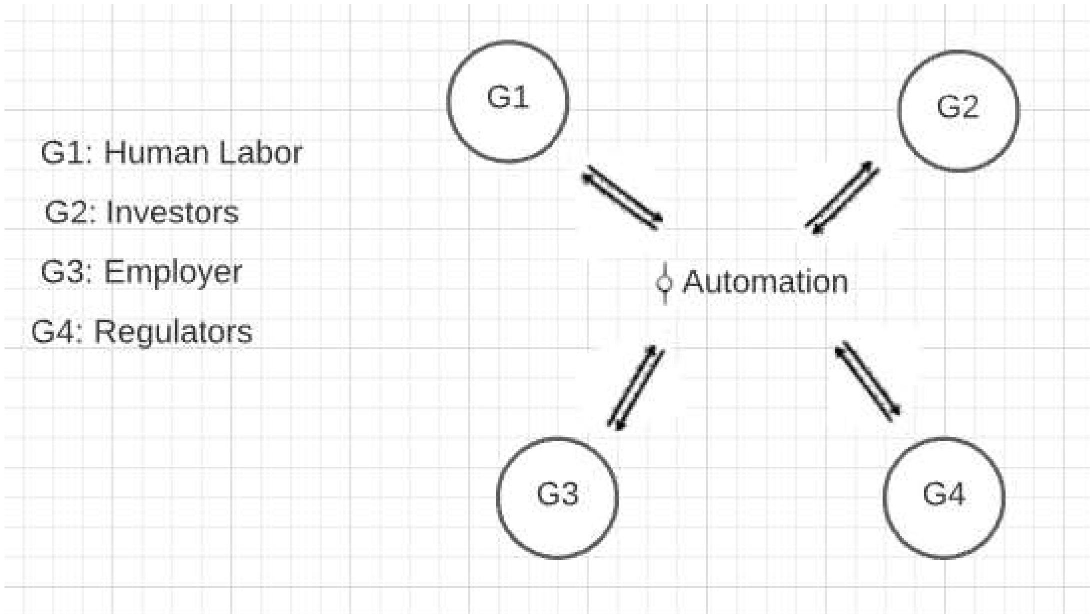

Figure 3: Social Construction of Technology Model for Automation. This model shifts the focus toward the relationship workers have with the automative technology and how the worker can then use the technology to improve their own productivity. This model emphasizes retaining laborers and instead of reducing cost maximizing productivity. (Bremer 2021)

laborers, investors, employers, and potentially even regulators have a say in how the automated technology is developed. This model is explicit in software development because a software developer has to take on the role of both worker and engineer. If there is a way to extrapolate this system to other forms of labor in order to grant laborers a greater voice in how the automation is developed a greater benefit can be found for all the parties involved. If laborers as a social group are given a greater voice in the development of technology they can retain their jobs and wages. Other relevant stakeholders such as businesses receive more productivity that mitigates the cost rather than having the same productivity with lower costs which in turn generates more revenue for investors. Some companies are already moving closer to this idea of robot-human cohabitation as noted by Lynch (2021). Lynch observes that Amazon designed the robot workers in their fulfillment centers with laborers in mind and that as a result has seen even higher productivity than ever before and has been hiring more workers while investing in more automation. It is important to also consider how regulators can potentially enforce this system by protecting the rights of workers who attempt to have a greater say in how the technologies which impact them are designed.

IMPACT ON VISIBLE HARM

This proposal of reframing how businesses, workers, and engineers approach automation could have a direct impact on the degree to which workers are displaced. Companies generally want to promote greater productivity and this system encourages maximized productivity. As productivity stays high the company should grow, and more growth will generally lead to more employment. However, this system is not guaranteed to prevent the displacement of workers, as the Government Accountability Office (2019) indicates it will always be a decision by the employer whether to increase productivity further or lower productivity by laying off more workers. The benefit of this system is that the input from the workers improves the usability of the automated technology in order to compensate for the cost of the laborers by improving productivity.

IMPACT ON INVISIBLE HARM

This model for understanding automation does help prevent several of the less noticeable and equally harmful aspects of automation. Having workers contributing to the automated system allows managerial networks and workers to function better together and would hopefully prevent the exploitation of the laborers by these systems which they help design. While algorithmic bias would not be completely eliminated, it would be significantly shifted in the worker's favor. Moral crumple zones would be easier to avoid as laborers would have a better understanding of systems that they help design. Elish (2019) points out that most of the catastrophic failures by automated systems are actually resulting from a failure by the laborer to understand why the system was reacting the way it was. With the systems being built to be in tune with the needs of the laborer this could very likely be prevented.

MOVING FORWARD

It is suspect to suggest that the displacement of laborers by automation is preventable but it is reasonable to suggest that it can be mitigated. Further research is required to lend credibility to the idea that automation performed in conjunction with the workers results in enough of an increase in productivity that labor costs are mitigated. Much more research needs to be performed into many of the areas tied to the invisible cost of automation. Problems such as algorithmic bias and improving managerial networks are still far from being solved and the proposed system of designing automated technologies does nothing to change that. As Lazio (2019) points out, the only long-term solution for automation seems to be a retraining of laborers to take on higher-skill labor positions. Lazio (2019) references 2.4 million unfulfilled STEM jobs currently on the market and describes how the biggest obstacle for low-skill laborers for making their way into these fields is the educational requirements. This problem has to be addressed, likely by improving the opportunities for laborers by granting them more access to educational courses on the subjects. Companies should be able to provide opportunities for growth for their employees which benefits both the laborers and the business. Transitioning low-skill workers to high-skill workers does not necessarily solve the problems of automation which will eventually displace even high-skill workers. But at the time it is unclear what future automation of labor promises and how we as a society can best change to benefit from it and move into an age of human-machine cohabitation.

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