Digital Transformation and Labor Market: How Much Do We Know?

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The pandemic made digital transformation a necessary practice to preserve and future-proof the business operation. International Data Corporation (IDC) expects spending on digital transformation in business will reach $2.8 trillion in 2025, more than double in 2020, to coalesce around operational objectives, including back-office support and infrastructure for core business functions such as accounting, human resources, legal, security and risk, and enterprise IT. Business benefits from digital transformation by improving efficiency, reducing cost, introducing new revenue channels, and meeting changing customer expectations (FinancesOnline). There are various definitions of digital transformation, often interchangeably used with "Industry 4.0," but all of them include "adoption and integration of digital technologies," including cloud computing, robotics, Blockchain, Artificial Intelligence (AI), Internet of Things (IoT), etc., which significantly enhance communication and connectivity. While it is an extension of the ongoing transition with "Industry 3.0" or IT and computer

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technologies, Industry 4.0 is fundamentally different in that it is based on the utilization of vast quantities of data for more flexible production.[1] Critically, recent advances in Machine Learning and Deep Learning in AI using ubiquitous massive data via mobile interface are remarkable, accelerating the pace of automation of cognitive tasks with high accuracy, which previously required high-skilled workers. Yet, we still live very far from artificial general intelligence, so it is too early to talk about the impact on the labor market; however, there is no doubt that the effect would be profound (Brynjolfsson and Mitchell 2017).

What do we expect to happen in the labor market? We can first learn some lessons from the adoption of robots (automation in general) that started earlier in the 1990s. Theoretically, automation reduces the labor share of value-added as capital (robots) replaces labor (displacement effect). At the same time, automation increases a firm's productivity and demand for labor (productivity effect). Importantly, technologies create new tasks in which labor has a comparative advantage, changing the task content of workers, and increasing labor share and demand (reinstatement effect) (Acemoglu and Restrepo 2019). Thus, the effect on the labor market becomes an empirical question and recent literature shows mixed results. For example, Graetz and Michaels (2018) find a positive impact of robot adoption on labor productivity growth and limited impact on total employment in 17 OECD countries. Dauth et al. (2017) present that the overall employment impact of robots in Germany was small because workers were able to relocate to the service sector, whereas Acemoglu and Restrepo (2020) find a robust decline in employment and wages in the US. Hence, regional variation exists; the displacement effect was larger than the productivity and reinstatement effect in the US while it was the opposite in Germany.

Along with what happened in the past, an ongoing debate exists over the future of the labor market, accompanied by fears of technological unemployment. Some research finds the fraction of workers in high automatable risk is substantial: 47% in the US (Frey and Osborne 2017) and 36% in Finland using occupation-level analysis (Pajarinen and Rouvinen 2014). On the other hand, Arntz, Gregory and Zierahn (2017) conduct a task-level analysis and show that only 9%, 6%, and 12% of the workers in the US, South Korea, and Germany, respectively, are at high risk, providing a much more optimistic point of view. In their paper, the authors assert that occupation-level analysis overestimates the automation risk because it ignores the large

[1] 1.0/2.0 technologies refer to mechanical or electrical technologies that are not IT-supported. 3.0 technologies are supported computers and software algorithms. 4.0-technologies are IT-integrated technologies including cyber-physical systems, Internet of Things, and smart technologies (Arntz, Greogry and Zierahn (2020).

variation in tasks within an occupation. Some workers in highly-automatable occupations already specialize in hard-to-automate tasks, and using the task composition of the representative worker fails to capture this heterogeneity and overestimates the risk.

Arntz, Greogry and Zierahn (2020) provide three reasons why automation and digitalization potentials must not be equated with actual employment effects. First, there is a gap between technological potential and its actual implementation because some of these technologies take time to diffuse in industries (technological diffusion). Second, workers do not stay static, but they learn new skills and adjust their set of tasks in response to automation (worker flexibility). Third, the introduction of new technology increases demand for labor because of complementarity to the new tasks and improvement in firm productivity (induced job creation). They further show a small but positive net employment effect due to 4.0 technologies in the middle-run, while there would be a negative employment change by the additional implementation of 1.0/2.0 and 3.0 technologies because firms are still in the early stage of investing in 4.0 technologies, in which complementary effects excel substitution effects.[2]

Nevertheless, large structural shifts between occupation and industries are inevitable. One important phenomenon in the labor market brought by computerization in earlier decades is wage and skill polarization. Because computers mostly displaced middle-skilled routine cognitive and manual tasks, the share of middle-waged and skilled workers declined with an increase in shares of high- and low-wage workers (Acemoglu and Autor 2011; Autor, Katz and Kearney 2006). Similarly, digital transformation will increase demand for highly cognitive and non-routine tasks, favoring high-wage workers, and rising polarization and inequality even more. Thus, while workers may relocate themselves to another job, the overall employment may remain relatively stable; however, the median wage may further decrease.

The important implication here is that worker mobility, especially to high-wage jobs, can be enhanced by education and training. Workers must learn how to use new technologies, and fortunately, technological advances would mitigate the difficulty by developing more intuitive systems and interfaces (Spence 2021).[3] More critically, education must focus on developing

[2] 4.0 industry technologies are general purpose technologies (GPT) that take time to diffuse in the economy. GPT requires complementary innovation and investment for productivity improvements and practical use. Thus, during the early period, substitution effect is much smaller than complementary effect in the labor market (Brynjolfsson and Mitchell 2017).

[3] For example, the home computer operating system was very difficult to learn when it was first introduced, and the transition from text-only to graphical user interface substantially lowered the barriers to using the computer.

skills in which workers hold comparative advantage – such as interpersonal interaction, flexibility, adaptability, and problem-solving – in addition to learning how to use new technologies. In other words, the human capital investment must have a long-term goal to build skills that are complementary rather than substitutable by technological changes (Autor 2015), making workers capable to “upskill.” However, skill development is often costly and time-consuming, and thus far from equitable, which makes policymakers consider implementing sophisticated education and worker training programs in partnership with businesses and schools.

Before we make dire predictions of the future, we must also answer the question of why there is a wide variation in change in employment and wage, and polarization across different markets in the past decades. For example, while automation negatively affected employment in the US in 1990-2007, there was limited effect in Germany. Arntz, Greogry and Zierahn (2020) suggest some potential reasons, such as labor market rigidity, vocational education, and average education level of affected workers. Disentangling the mechanism behind this variation must be the primary future research area for the labor market to get prepared for the unprecedented structural change coming with the inevitable wave of Industry 4.0. In addition, further studies need to be conducted regarding the impact on emerging markets as we expect both positive and negative effects. While investment in digital technologies may create new economic opportunities in developing countries, digital transformation in developed economies may induce reshoring and harm the labor markets in emerging markets (ILO 2020); however, there is still significantly less attention to developing economies. KIEP

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