Which Tasks Will Technology Take? A New Systematic Methodology to Measure Task Automation

Research-in-Progress

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Abstract

With the rapid advance of digital technologies, task automation has recently come to the forefront of the debate on skill-biased technological change. Building on a network theory, this study develops a new systematic methodology to identify comprehensive task types in the overall economy, and to quantitatively measure the degree of automation for each task type. Using comprehensive dataset on occupational skill requirements in 2015, we construct a two-mode network, and identify 13 task types using a non-parametric clustering algorithm. Our findings suggest that routine cognitive task and information processing are most automated tasks, and that flexible thinking and dynamic physical task are least susceptible to automation in 2015. The major contribution of our approach lies in the estimation of degree of automation for different task types. The methodology presents a promising avenue for evaluating the impact of automation on labor market outcomes, such as wage inequality and job polarization.

Keywords: Network analysis, two-mode network, automation, skill-biased technological change, societal impacts of IS

Introduction

"Current trends could lead to a net employment impact of more than 5.1 million jobs lost to disruptive labor market changes over the period 2015-2020..."

- World Economic Forum (Leopold et al. 2016)

With the rapid advance of technologies, automation has recently come to the forefront of the debate on skill-biased technological change (SBTC) (Brynjolfsson and McAfee 2011). Since information technology (IT) has advanced tremendously in the past few decades, it has been blamed for this societal challenge. Brynjolfsson and McAfee (2014) highlight the exponential growth in digital technologies, referred to as Moore's Law, and discuss the disruption to labor markets introduced by technological innovation over the period of what they have characterized as "second-half" of exponential growth. Frey and Osborne (2013) suggest that about 47 percent of total U.S. employment is at risk from computerization. On the other hand, Bessen (2016) argues that new computer technologies increase wage gaps by shifting employment and requiring new skills, rather than eliminating jobs. In line with these works, this study aims at contributing to this topic that has been subject to much debate among policy makers and researchers.

The extant literature in SBTC has paid attention to the degree of automation in order to examine the labor market outcomes, such as wage inequality and job polarization which have been remarkable phenomena since the 1990s (Acemoglu and Autor 2011; Van Reenen 2011). In particular, given that computers could automate a specific task rather than a job *per se*, it is important to investigate the research question in assessing the impacts of automation on jobs and wage structures: Which tasks have been or not been automated by technologies?

However, previous studies have limitations in several ways. Firstly, these studies attempt to categorize skill sets or task types, *a priori*. Despite distinct merits of theory-driven approach, they are possibly subjected to *ex ante* biases. For instance, Autor et al. (2003) propose a task model in which tasks are divided in two dimensions: *routine* versus *non-routine* and *cognitive* versus *manual*. Elliott (2014) separates the capabilities into four general areas which can be compared to human capabilities: *language, reasoning, vision,* and *movement*. However, their task classifications tend to be subjective and not comprehensive, leading to different conclusions from different studies. In addition, predefined skill sets might not be appropriate in the era of rapid technological advance because the nature of tasks occupations undertake has changed over time (MacCrory et al. 2014).

More importantly, prior literature does not provide important insights about how much tasks are automated, possibly due to a lack of appropriate methodology and data. In the absence of a relevant measure, previous studies rely on a logical inference or subjective judgements about susceptibility to automation. For example, Autor et al. (2003) suggest that *routine tasks* are vulnerable to automation, whereas *non-routine tasks* are complementary to technologies. However, they do not answer to the critical questions: Which *non-routine cognitive tasks* are more complementary to automation, *analytical* or *interpersonal*? While there is anecdotal evidence mentioning the new characteristics of automation, we have limited understanding of the nature of tasks and degree of automation (see Brynjolfsson and McAfee (2014) for broad discussion on technological advance and their consequences in the digital economy).

To fill such voids, this study develops a new systematic methodology to identify comprehensive task types in the overall economy, and to quantitatively measure the degree of automation for each task type. Using comprehensive dataset on occupational skill requirements for 651 jobs from O*NET, our data-driven approach rules out *ex ante* inference bias and provides more comprehensive view of task types performed by occupations in the overall economy. To achieve two main goals of identifying task types and measuring the degree of task automation, we construct a two-mode network, namely "job-skill network," in which jobs and skills are two classes of nodes. Then, the two-mode network is projected to a one-mode network, namely "skill network," whose weights of edges between skill nodes are the skill correlation which represents latent interdependence among skills. From the skill network, we identify 13 task types using a non-parametric clustering algorithm.

It is worth noting that this dataset provides a measure of "degree of automation" for each *job*, allowing us to directly measure the degree of automation for each *skill*, thereby for each *task*. In this study, the degree of automation for each *skill* is defined as the degree of how much the focal skill is correlated with the degree of job automation. If a skill is required proportionally to the degree of job automation across occupations, this skill can be considered to be highly automated. For each *task type*, which is a cluster of interdependent and relevant skills, we measure the degree of automation by averaging measures of skill nodes which belong to the task.

By applying this methodology to O*NET datasets, our findings suggest that *routine cognitive task* and *information processing* are most automated tasks, and that *flexible thinking* and *dynamic physical task* are least susceptible to automation in 2015. To the best of our knowledge, this is the first study to quantitatively measure the degree of automation for task types. We believe that this study would provide a solid foundation for future empirical research and practice, as long as the source dataset continues to be updated. Our measure of degree of automation can be applied to investigate the impacts of SBTC and automation on wage inequality and labor market outcomes. Moreover, the systematic methodology proposed in this study can allow researchers and policy makers to "track the development of the (technological) capabilities and anticipate the full range of their consequences" over time (Elliott 2014).

Literature Review

> *"Digital technologies change rapidly, but organizations and skills aren't keeping pace. As a result, millions of people are being left behind. Their incomes and jobs are being destroyed…"*
>
> - *Race Against the Machine*, Brynjolfsson and McAfee (2011)

SBTC is a shift in technologies that favor skilled over unskilled labor by increasing its relative productivity, and thus its relative demand (Autor et al. 1998). SBTC has maintained upward pressure on the demand for highly skilled and educated workers while many lower skilled jobs have disappeared and median incomes have stagnated, contributing to increasing inequality (Acemoglu 1998; Machin and Van Reenen 1998). Recent studies suggest that IT complements skilled labor (Autor et al. 1998; Bresnahan et al. 2002; Michaels et al. 2014; Park and Lee 2016). Bresnahan et al. (2002) show how the sharp decline in IT prices leads to a cluster of changes in IT use, organizational practices, and product innovation, thereby increasing the demand for skilled labor. According to Frey and Osborne (2013), educational attainment is negatively associated with an occupation's probability of computerization. Michaels et al. (2014) suggest that IT has contributed to the decline in the demand for middle-skilled jobs by substituting for rule-based routine tasks.

The disruption of jobs is introduced by technological innovation when certain tasks can be performed by technology and no longer need to be performed by workers (Autor et al. 2003). Given that computers could automate a specific task, which is a cluster of relevant skills, rather than a job *per se*, previous studies segment the workforce into skill categories or task types, in assessing the impacts of automation on jobs and wage structures (See Table 1 for task classifications in the extant literature). Autor et al. (2003) propose a task-based model, separating tasks in two dimensions: *routine* versus *non-routine* and *cognitive* versus *manual*. The model predicts that IT contributes to the job polarization by automating and substituting for the *routine tasks*, mainly executed by middle-skilled occupations (e.g., production workers and clerks) (Acemoglu and Autor 2011; Autor et al. 2003; Michaels et al. 2014). On the other hand, IT is likely to increase the demand for *non-routine cognitive tasks* of high-skilled workers (e.g., managers). Since it is not yet easy to use IT to automate *non-routine manual tasks* requiring hand-eye coordination and responses to the unforeseen, IT has largely not affected the relative demand for low-skilled workers performing non-routine manual tasks (e.g., hairdressers).

Table 1. Task Classifications in the Extant Literature

Autor et al. (2003)	Routine cognitive, routine manual, non-routine cognitive (analytical / interpersonal), non-routine manual
Frey and Osborne (2013)	Manipulation, creative intelligence, social intelligence
MacCrory et al. (2014)	Cognitive, manual, supervision, interpersonal, initiative
Elliott (2014)	Language, reasoning, vision, movement
Deming (2015)	Routine, non-routine analytical, social skill, service

Frey and Osborne (2013) suggest that "engineering bottlenecks" create three categories of tasks that are not susceptible to automation: *perception and manipulation tasks, creative intelligence tasks*, and *social intelligence tasks*. Based on these task compositions, Frey and Osborne calculate an occupation's probability of computerization, arguing that about 47 percent of total U.S. employment is at risk from computerization. However, they rely on subjective judgements about susceptibility to automation (McAfee and Brynjolfsson 2016), and do not focus on tasks' probability of computerization or automation, which is our main focus.

Prior literature has several limitations to be addressed in this study. First, task classifications in previous studies are "defined a priori, and are thus limited by the assumptions inherent in logical inference" (MacCrory et al. 2014). Although theory-driven approaches have well explained the patterns and underlying mechanism of the labor market, their task classifications tend to be subjective and not comprehensive, leading to different conclusions from different studies. In addition, since the nature of tasks has also rapidly evolved, predefined skill sets might not be appropriate to assess the impacts of automation in the era of rapid technological advance. Using a data-driven approach, this study aims to rule out *ex ante* inference bias and provide more comprehensive view of task types performed by occupations in the overall economy.

Second, previous studies do not provide important insights about how much tasks are automated, possibly due to a lack of appropriate methodology and data. In the absence of a relevant measure, previous studies rely on a logical inference or subjective judgements for the degree of automation. For example, Autor et al. (2003) suggest that *routine tasks* are vulnerable to automation, whereas *non-routine tasks* are complementary to technologies. However, they fail to elucidate the impacts of automation on tasks, and thus it is ambiguous whether *non-routine analytical* or *interpersonal tasks* are more complementary to automation. This study develops a systematic methodology to quantitatively measure the degree of automation, helping to track the impacts of technological advance in terms of task automation.

Of most relevance to our study is the work of MacCrory et al. (2014), which attempts to derive orthogonal skill sets using a data-driven approach. By performing principal component analysis (PCA), MacCrory et al. identify 5 orthogonal dimensions using dataset on occupational skills in 2014: *cognitive, manual, supervision, interpersonal,* and *initiative*. Our work differs from MacCrory et al. (2014) in several important ways. First and most importantly, while they examine the change in task compositions over time, MacCrory et al. do not provide a relevant answer to the question of which tasks are subject to be automated. Second, contrary to the PCA approach, our network-based approach allows to uncover and visualize the underlying task structures and relationships between tasks, as discussed in Methodology session.

Conceptual Framework

One challenge to identify task types is that they are not directly observed from labor statistics. In this section, we discuss a conceptual framework of skill, task, and job to lay the groundwork to reveal task types using data about jobs and skills. While the terms of job, task, and skill are usually used interchangeably in SBTC literature, we conceptualize the hierarchical relationship between them (See Figure 1). A *job* is required to perform a set of *task types*. *Tasks* are broadly defined as the actions carried out by individuals in turning inputs into outputs (Goodhue et al. 1995). Goodhue et al. (1995) define technologies as tools in carrying out individuals' *tasks*. In that sense, technologies could automate and substitute for task types, rather than jobs *per se*.

Each task type can be accomplished with a set of relevant skills. *Skills* are defined as abilities and capacities to carry out complex *tasks* or job functions. While we cannot directly observe task types performed by occupations, this framework allows us to identify task types. According to this framework, a task type can be redefined as a cluster of highly correlated skills across jobs. If two skills tend to be highly required for same jobs, these skills will be classified into a same task type.

In addition, prior literature has largely neglected how tasks are interrelated with each other. However, not only task characteristics, but also these relationships between tasks might play an important role in shaping the job structures. For instance, Hasan et al. (2015) suggest that task interdependencies influence the dynamics of job structures. In our framework, two tasks which require similar skill sets will be closely related with each other. In Figure 1, for example, *task type 1* tends to have something in common with *task type 2*, whereas it may have quite different characteristics from *task type 3*. Understanding the structure of task relationships, as well as identifying task types, can provide deeper understanding of the nature of tasks, and help to categorize the identified task types.

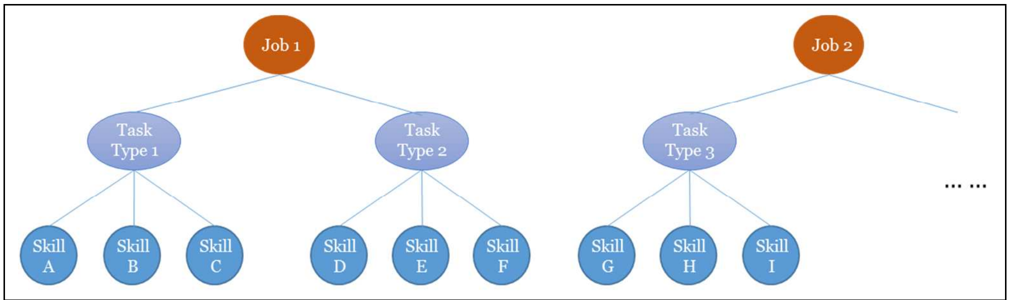

Figure 1. Conceptual Framework of Skill, Task, and Job

Methodology

Data

We use O*NET database, which is one of the most comprehensive data on occupational skill requirements, developed by the National Center for O*NET Development and sponsored by the U.S. Department of Labor.[1] Many previous studies in SBTC use this dataset (e.g., Acemoglu and Autor 2011; Deming 2015; MacCrory et al. 2014; Park and Lee 2016). This database provides job characteristics and skill requirements, for 974 representative occupations in the economy. We exclude some occupations, whose codes are not comparable with Standard Occupational Classification (SOC) system, leaving 651 occupations.[2]

In this study, we broadly define skills as job descriptors in the category of Abilities, Work Activities, Skills, and Work Contexts, as compiled by O*NET, to maintain comparability with prior literature (e.g., Acemoglu and Autor 2011; MacCrory et al. 2014).[3] As a result, 182 skills are included in the analysis.[4] Each skill is rated by trained occupational analysts and by job incumbents. The importance scale is used to be consistent with prior literature, which indicates how important a particular skill is to the occupation which ranges from one ("Not important") to five ("Extremely important"). We normalize skills' degree of importance with mean zero and standard deviation one.

We use the version 20.0 of O*NET database published in August, 2015. The database is regularly updated for approximately 10%-15% of the occupation information (MacCrory et al. 2014). All occupations were updated at least once since its initial version in 1998. Thus, our findings in this study would reflect the most recent relationship between jobs, tasks, and technologies.

Two-mode network analysis

Network (or graph) theory has been employed to uncover and visualize the underlying structure in the data, in broad areas of biology, physics, mathematics and social science (Bonanno et al. 2003; Dusser et al. 1987; Mantegna 1999; Mizuno et al. 2006; Naylor et al. 2007; Onnela et al. 2002; Tumminello et al. 2007). Specifically, the minimum spanning tree (MST), which connects all the nodes together with the minimal total weighting for its edges, has been used for that purpose. Especially noteworthy is that Mantegna (1999) reveals the *unobserved* hierarchical structures of financial markets by applying MST to

[1] O*NET Database, http://www.onetcenter.org/db_releases.html

[2] The SOC system is used by Federal statistical agencies to classify workers into occupational categories for the purpose of collecting, calculating, or disseminating data. All workers are classified into one of 840 SOC occupations according to their occupational definition. O*NET devises the O*NET-SOC code by including 270 new sub-codes to account for new and emerging occupations. For example, while all chief executives are included in the SOC code 11-1011, O*NET supplements a new job, chief sustainability officers as a code 11-1011.03. Of 840 SOC occupations, O*NET maintains data on 704 major occupations in 2015 excluding most "All Other" categories. Some occupations also drop for comparability because of the change in occupational classification systems. Finally, we have 651 occupations in our dataset which account for 80.0 percent of total U.S. employment in 2015.

[3] We exclude other categories in O*NET database, such as Work Values and Work Style, because they represent personal characteristics, rather than skill requirements in which technology can play a critical role.

[4] To be consistent with Acemoglu and Autor (2011), the scale of *Structured versus Unstructured Work* is reversed.

the stock price correlations. Naylor et al. (2007) investigate the dynamic topology of foreign exchange market based on MST. Thus, we build on a network theory to identify task types in the overall economy and to quantitatively measure the degree of automation for each task type.

A two-mode network (also known as affiliation or bipartite network), which is a particular type of networks with two classes of nodes and ties are only established between nodes belonging to different classes, provides an appropriate way to represent our research setting. In this study, jobs and skills are two classes of nodes, and we define the two-mode network as "job-skill network." The weight of edges between job and skill indicates how important a particular skill is to the job.

One approach to handling two-mode network is to project it into an one-mode network because most network measures are solely defined for one-mode networks, and only a few of them have been redefined for two-mode networks (Borgatti 2009; Borgatti and Everett 1997; Latapy et al. 2008). We refer to the one-mode network as "skill network," and the projection process is depicted in Figure 2. For a goal of projection, we define a skill correlation as the average product of a pair of edges linked to the same job. More formally, for *Skill A* and *B*, we calculate the skill correlation ρ_{AB} as $\frac{\sum_{i=1}^{n} w_{iA} w_{iB}}{n}$, where w_{iA} and w_{iB} is the importance of *Skill A* and *B* to *Job i*, respectively. The skill correlation becomes an edge between two skills in the skill network. Note that our definition of skill correlation corresponds to the definition of Pearson correlation which ranges from -1 to 1, because we normalize the degree of importance with mean zero and standard deviation one. Thus, positive skill correlation between two skills means that these skills are closely correlated with each other across jobs. Conversely, if they have negative value, then two skills are unlikely to be required in same jobs, that is, they are negatively correlated. If the skill correlation is close to zero, they have erratic relationships across jobs, implying that they are uncorrelated.

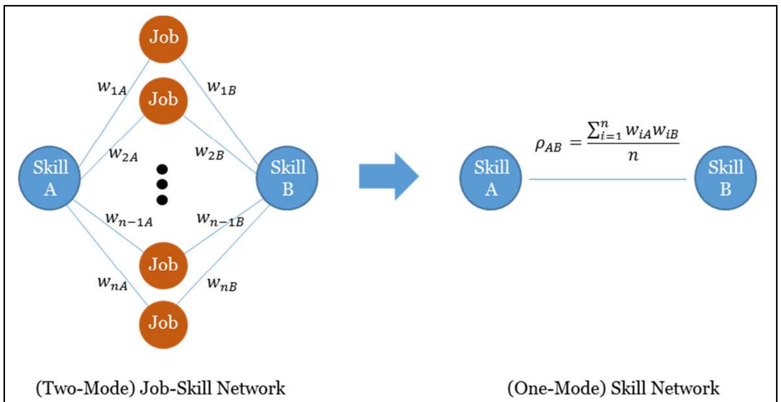

Figure 2. Projection from Two-Mode to One-Mode Network

Since the skill network are a kind of complete graph, we construct the MST of the skill network to uncover the underlying structure with only important edges being connected. Firstly, we transform the skill correlation between skill nodes into a distance measure by converting the matrix of skill correlation into the inverse. More formally, we define the skill distance as $d_{AB} = \frac{1}{\rho_{AB} + |\min(\rho_{ij})| + \varepsilon}$, where $\min(\rho_{ij})$ is the minimum of skill correlation for every skill $i, j \in [1, n]$ and $i \neq j$. To avoid indivisible cases, we add very small constant number to every numerator, denoted as ε. By defining the distance in this manner, we place a more importance on edges which have high skill correlations. Then, we use Kruskal's algorithm to construct the MST of the skill network.

After constructing the MST, to identify task types in the skill network, we employ a non-parametric clustering algorithm, the Louvain method, developed by Blondel et al. (2008). The Louvain method has been used to identify communities, or clusters, in networks, with success for networks of many different types and for sizes up to 100 million nodes and billions of links. For instance, Greene et al. (2010) apply this method to mobile phone networks to suggest the strategy for tracking communities which persist over time with 4 million nodes and 100 million links.

Measurement of automation

It is worth noting that O*NET provides a measure of "degree of automation" for each *job*. It allows us to measure the degree of automation for each *skill*, thereby for each *task*, which is main focus of this study. The measure of job automation indicates how automated the job is, which ranges from one ("Not at all automated") to five ("Completely automated").

In this study, we define the degree of automation for each *skill* as the correlation between the node of "degree of automation" and the skill node, as defined in the same way discussed above. This measure provides the degree of how much the focal skill is correlated with the degree of job automation. If a skill is required proportionally to the degree of job automation across occupations, this skill can be considered to be highly automated. For each *task type*, which is a cluster of interdependent and relevant skills, we measure the degree of automation by averaging the measures of skill nodes which belong to the task. Tasks with positive (negative) value correspond to those which are (not) susceptible to automation.

Results of Network Analysis

Figure 3 illustrates the MST of skill network grouped by task types, a cluster of relevant skills. Using a clustering algorithm, we identify 13 task types, and designate the names of task types, based on their skill components (See Table 2 for details).

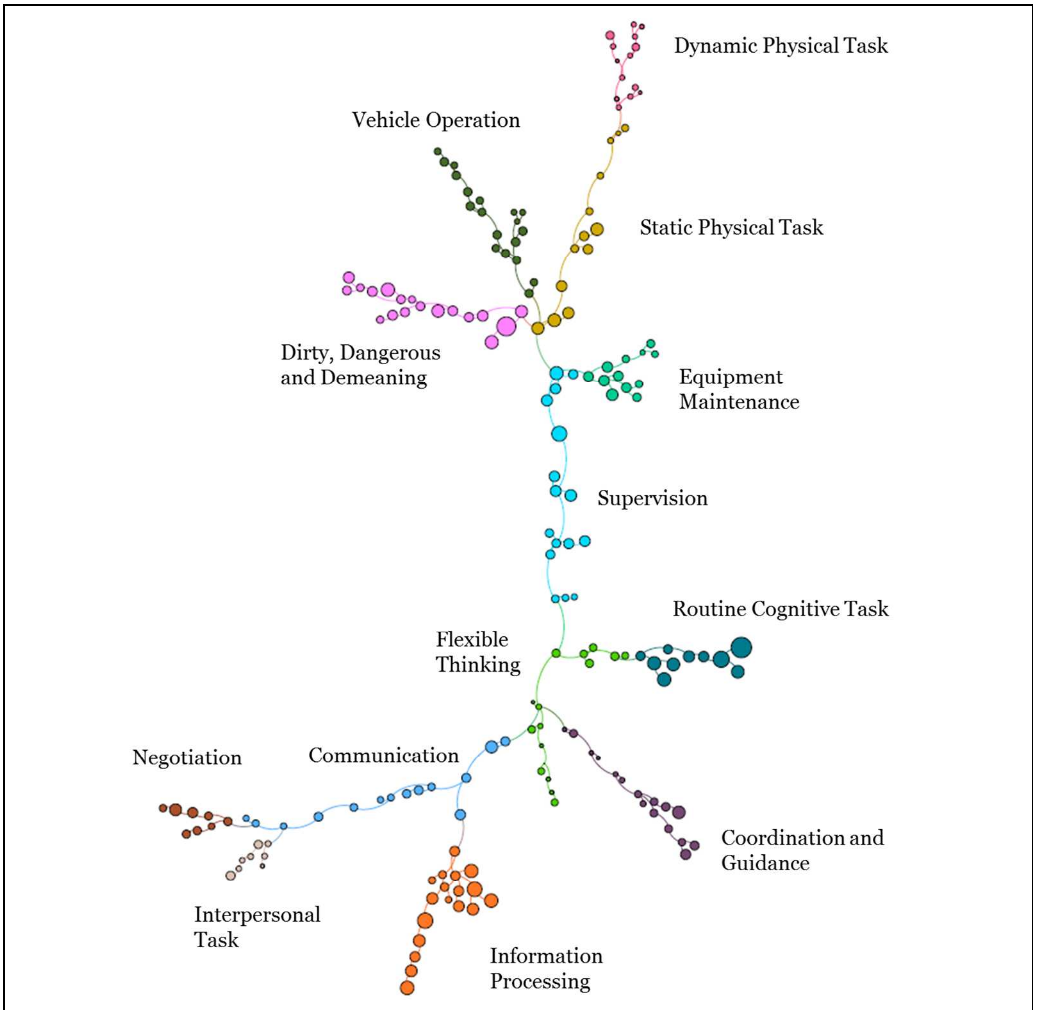

Figure 3. One-Mode Skill Network in 2015 [5]

[5] Task types, which are skill clusters, are illustrated in different colors, and the size of node represents the degree of automation.

In a tree structure, relevant skills and its clusters tend to be sibling nodes which share the same parent node. In Figure 3, for example, *dynamic physical task* is more correlated with *static physical task*, than *information processing*. *Communication*, *negotiation*, and *interpersonal task* are closely related with each other. Reasonably, the skill network can be divided into cognitive and manual tasks by their tree structure. Manual tasks include *dynamic physical task*, *static physical task*, *dirty, dangerous, and demeaning*, *vehicle operation,* and *equipment maintenance*. Cognitive tasks include *supervision, routine cognitive task, flexible thinking, coordination and guidance, information processing, communication, negotiation,* and *interpersonal task*.

Table 2 presents the degree of automation for each task type. Our findings suggest that *routine cognitive task* and *information processing* are most automated tasks, and that *flexible thinking* and *dynamic physical task* are least susceptible to automation in 2015.

Table 2. Task Types and Degree of Automation

Task Types	Representative Skills	Degree of automation (%)
Routine Cognitive Task	• Importance of Repeating Same Tasks • Information Ordering • Number Facility	16.42
Information Processing	• Analyzing Data or Information • Processing Information • Interacting With Computer	8.57
Dirty, Dangerous and Demeaning	• Wear Common Protective or Safety Equipment • Exposed to Hazardous Equipment • Pace Determined by Speed of Equipment	6.41
Supervision	• Operation Monitoring • Auditory Attention • Frequency of Decision Making	4.50
Static Physical Task	• Static Strength • Controlling Machines and Processes • Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls	0.68
Equipment Maintenance	• Equipment Maintenance • Repairing and Maintaining Electronic Equipment • Troubleshooting	-0.73
Negotiation	• Negotiation • Frequency of Conflict Situations • Resolving Conflicts and Negotiating with Others	-1.24
Communication	• Social Perceptiveness • Speech Recognition • Oral Comprehension	-2.99
Vehicle Operation	• Operating Vehicles, Mechanized Devices, or Equipment • Spatial Orientation • Sound Localization	-5.23
Coordination and Guidance	• Coordinating the Work and Activities of Others • Developing and Building Teams • Guiding, Directing, and Motivating Subordinates	-7.01
Interpersonal Task	• Performing for or Working Directly with the Public • Deal with External Customers • Contact With Others	-10.91
Flexible Thinking	• Thinking Creatively • Developing Objectives and Strategies • Freedom to Make Decisions	-12.00
Dynamic Physical Task	• Dynamic Strength • Dynamic Flexibility • Gross Body Equilibrium	-14.60

Discussion and Future Work

Our task types are largely corresponding to those in the extant literature, though previous task classifications account for only part of ours. For instance, *non-routine interpersonal task* in Autor et al. (2003) corresponds to *coordination and guidance,* based on its skill components. *Supervision* task is largely similar to that identified by MacCrory et al. (2014). *Interpersonal task* and *negotiation* are corresponding to *social intelligence*, proposed by Frey and Osborne (2013). Hence, our task classification provides more comprehensive picture of task types performed by occupations in the overall economy.

Our methodology can complement the extant literature on impacts of technological change. For instance, the task model of Autor et al. (2003) is one of the most cited classifications to investigate how SBTC has influences on employment and wages (e.g., Acemoglu and Autor 2011; Michaels et al. 2014). Based on our results, we calculate the degree of automation for task types proposed by Autor et al. (2003). In Table 3, the results show that despite *a priori* reasoning, the task classification of *routine* versus *non-routine* has successfully explained the degree of automation across occupations. As suggested in the task model, *non-routine cognitive tasks* are substantial complementary to automation, and technologies are largely not affected the *non-routine manual tasks*. In contrast, technologies have substantially substituted for *routine tasks*, both *manual* and *cognitive*. Of non-routine cognitive tasks, *non-routine interpersonal tasks* are a little more complementary to automation than *non-routine analytical ones*.

It is worth noting that *non-routine analytical tasks,* treated as a homogeneous task in Autor et al. (2003), are split into *flexible thinking* and *information processing* in our classification.[6] Since they are not homogeneous in terms of degree of automation, they are required to be considered separately in assessing the impacts of automation on jobs. Thus, these results suggest that there is a need to elaborate task classification to properly consider heterogeneous degree of automation.

Table 3. Degree of Automation in Autor et al. (2003) [7]

	Degree of automation (%)
Non-routine cognitive (interpersonal)	-11.58
Non-routine cognitive (analytical)	-9.08
Routine cognitive	31.85
Routine manual	24.09
Non-routine manual	-3.17

This paper aims to make a few key contributions to the literature. First, to the best of our knowledge, this is the first study to quantitatively measure the degree of automation for task types. An old management adage, “if you can’t measure it, you can’t manage it,” explains why the measurement of automation is so important in the digital economy. Given that the degree of automation ultimately affects the employment and wage structures, our measure of automation for each task type can be applied to investigate the impacts of SBTC on wage inequality and job polarization, which have been a remarkable pattern in the labor market since the 1990s (Van Reenen 2011). We believe that this study would provide a solid foundation for future empirical research and practice, as long as the source dataset continues to be updated.

Second, Elliott (2014) argues that “systematic reviews need to be carried out once or twice each decade to make it possible to track the development of the capabilities and anticipate the full range of their consequences.” This study is expected to provide a systematic methodology for researchers and policy makers to investigate the impacts of technological change over time. In particular, O*NET database is regularly updated since 1998, allowing us to examine structural changes in the skill network during the last decade. In future work, we expect to answer several research questions: 1) Which task types have become substitution or complementarity to technologies in the last decade? 2) Are there any systematic directions of technological advance in terms of automation?

[6] According to Acemoglu and Autor (2011), *non-routine analytical tasks* are composite of “Analyzing data/information,” “Interpreting information for others,” and “Thinking creatively.” However, the first two skills are included in *information processing*, and the last one is included in *flexible thinking*.

[7] See Acemoglu and Autor (2011) for the task measures, based on O*NET scales.

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