Social Glue and Post-COVID Labour Markets: Evidence from a Task Census of a Large Corporation

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Abstract. This research analyses the text of the complete set of job descriptions for a large corporation to produce a census of tasks useful for modelling likely technology-enabled changes to work. After briefly explaining the method for producing the task census, we describe a theme of tasks that appear widely in jobs not only across units, but also up and down the hierarchy. To summarize this finding, we call it social glue because the recurring tasks tend social ties that facilitate information exchange essential to performance of both individual jobs and the organization overall. In discussion of what social glue means for the future of work in a post-COVID world, we suggest the current rapid adoption of video-calling technologies and collaboration tools has already laid a foundation for new approaches to social glue that will have profound and lasting implications for job design, organization structure, and commuting patterns.

Introduction

Public intellectuals have written widely of a new industrial revolution (e.g., Schwab 2015) in which technologies derived from artificial intelligence (AI) research will displace large chunks of current workforces, forcing development of new kinds of work. In the original industrial revolution, the percentage of the population working in agriculture from two-thirds in Britain and three-quarters in the United States to less than 5% in both countries; this took just over a century. In a widely cited study by (Frey and Osbourne 2013), an analysis of jobs data from the US Department of Labor predicts 47% of jobs in the US economy are at high risk of AI-based automation over the next several decades.

What might such changes mean for organisation design? By law and as a matter of economic theories of the firm, an organisation is a nexus of contracts that organises essential activities into a hierarchy while relying on up- and downstream markets for goods and services deemed (Williamson, 1975). In economics, the boundaries of firms are theorized to a search for minimizing the transaction costs of activities by organizing them into a hierarchy or leaving them to markets (Coase 1937, North 1990, Williamson 1994). In organization studies, organization designs historically followed an engineering logic for smoothing task interdependencies (March and Simon 1958, Thompson 1967) and managing risks arising from dependence on critical resources (Pfeffer and Salancik 1978).

Over the last generation, however, theory has explained shifts in the prevalence of particular organizational forms and designs as a function of pressures to fit institutional environments that reward forms that seem not only more legitimate than others (DiMaggio and Powell 1983, Meyer and Rowan 1977), but also more valuable to investors (Zuckerman 1999). For example, the former fashion of conglomerate diversification all but died away (Davis, Diekmann and Tinsley 1994) as managers and investors finally embraced the idea from finance that investors can diversify more cheaply for themselves (Modigliani and Miller 1958). As organizations were being thusly remade, the rise of globalisation and outsourcing combined to lead scholars and practitioners alike to use relatedness (Barney and Hoskisson 1990, Hoberg and Phillips 2010) and synergies of related resources as a key criterion for selecting what to include in an organisation (Penrose, 1959; Prahalad and Bettis, 1986; Prahalad and Hamel, 1990).

As organization designs shifted away from conglomerate diversification that smoothed earnings to tight relatedness to realize synergies, we argue this shift combined with the adoption of new data resources and information systems to fuel the rise of a new kind of work that we call social glue. As we will elaborate below, social glue is especially in cognitive work that facilitates productive exchanges of information and insights between the people and operations of an organization's interdependent functions and subunits. We conceptualize these exchanges as generalized social exchange as opposed to reciprocal social exchange (Ekeh 1974). This is because the information flows that support individual and organizational performance depend not only on strong dyadic ties, but also on the circulate of information in longer, more circuitous communication pathways.

To be clear, we arrived at the idea of social glue inductively in the course of analysing the text of the complete set of job descriptions of a large corporation; these analyses were part of a larger project aimed at understanding how the future of work could be affected by breakthroughs in data science (DS), machine learning (ML), artificial intelligence (AI), and robotics, among others. As mentioned in our abstract, these analyses allowed us to create a census of tasks, and the concept of social glue is our interpretation of a collection of tasks that recur widely in job descriptions that span the breadth of the organization's subunits and the full depth of its hierarchy.

The paper is organized as follows. First, we describe the context, data and methods for the task census. Second, we summarise findings of the data reduction exercise that led us to posit the social glue concept. Third, we discuss the importance of social glue and speculate about what it might look as organizations are work, jobs, and organization structures are redesigned in response to adoption of technologies that automate and augment human work with tools that, at least in some cases, may be designed with human-like interfaces that both permit and demand new approaches to social glue.

Context

The concept of social glue emerged from analyses for a larger project to forecast how coming technologies—especially AI and robotics— will affect jobs and the future of work. This project was done in collaboration with the advanced technology unit of a large industrial corporation. The work builds on an earlier publication that described methods for visualising technology-related changes to future workforces of a large bank (Amador Diaz Lopez, Mollina-Solana and Kennedy 2018).

Following Autor (2013) and Bessen (2018), our approach to the analyses of the broader project proceeds from the view that a job is a bag of tasks. This view of jobs is particularly important to organisation theory and organisation design because it suggests a familiar path to managing the adoption of AI-based changes to organisations that have been widely described as revolutionary (Schwab, 2015). While technologies sometimes create opportunities to substitute capital for all the tasks bundled into the bag of tasks for a particular job, technologies are more likely to take over some tasks while related jobs are redefined to include new ones demanded by evolving strategies for delivering related goods and services. Google's Chief Economist, Hal Varian, puts it this way: "Automation doesn't generally eliminate jobs. Automation generally eliminates dull, tedious, and repetitive tasks. If you remove all the tasks, you remove the job. But that's rare."[1] Thus, while we have

[1] Conference at Stanford Center for Human AI; summary article from March 7, 2019. https://www.gsb.stanford.edu/insights/misplaced-fear-job-stealing-robots

a few examples in which a technology eliminates a whole job (think elevators and elevator operators), there are many more examples where technologies replace part of the workload of a job (think ATMs and bank tellers). Even when all of a job seems to be replaced by a technology, there are usually task from that job's bag of tasks that migrate to other jobs—other bags of tasks. With elevator operators, for example, tasks like greeting customers, answering questions, and keeping a watchful eye out for theft shift are nearly always still performed—only now by people in other jobs. And when technologies do some of a job's tasks while leaving others for people still to do, the result is usually to have fewer people in the job. With bank tellers, for example, there are fewer today than a generation ago, and in many banks, the job of a teller is a more varied bag of tasks than it once was.

Data and Methods

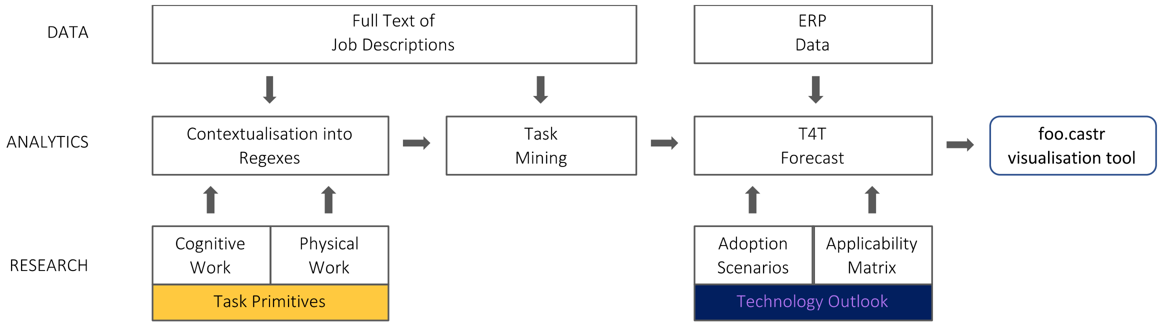
Through secure file transfer and under contract with provisions for secure storage and limited access, we received the following unstructured and structured data.

- *Unstructured data:* Full text of the complete set of job descriptions for the whole corporation, globally; this was roughly 1,600 job descriptions. Each job description had a summary of skills and a list of detailed responsibilities (tasks).
- *Structured data:* HR data including headcount and location by job along with the superordinate group designations that situate each job in the overall organisation chart.

To produce the task census that is the focus of this paper (and to be able to do the forecasts of our wider project), we developed a tools-for-tasks method for relate technology-derived tools to the tasks that make up a job. The numbered list below summarises the major elements and steps of the method, and Figure 1 illustrates how these are combined, at a high level, procedurally. For a first round of forecasts in the wider project, we use the contextualisation step (3) to write regular expressions that accurately the task primitive concepts in the task mining step (4). In ongoing work, we are developing more advanced task mining approaches that will rely less on contextualisation, which is laborious.

1.	Task primitives:	Theory-based view of building blocks of cognitive and physical work
2.	Contextualisation:	Match language of job descriptions to task primitive concepts
3.	Task mining:	Text mining reduces job descriptions to a task primitive vector (TPV) whose values score the presence of each task primitive in the job
4.	Technology outlook:	Catalogue tech tools likely to automate or augment human work
5.	Adoption scenarios:	Create scenarios that vary timing and extent of technology adoption
6.	Tools-for-tasks:	A technology applicability matrix (TAM) links tools, task primitives
7.	Forecasts:	Use TAM, TPVs, and scenario adoption curves to compute job-level impact and aggregate up into impact by organizational subunit
8.	Visualisation:	Distill results into interaction visualisation

FIGURE 1: Steps in the proposed tools-for-tasks method



Overview of Results

To situate the social glue concept in the wider project, we present visualisations of forecasts for two scenarios; see Figures 2 and 3 below.

To explain the charts, the ten columns are each 2 of 20-years in a forecast window from 2020 to 2040. The bands in the first column represent the relative share of the total company workforce in the organization's top-level units. In column 1 (time 0 to time 1), the bands at the left edge represent the proportion of the total workforce in each of the company's top-level subunits at time 0. Moving from the left to right edge of the first column, we see slender chords flow from bands for each subunit into colored bands that represent the share of task-level work being picked up by technologies aggregated into the following four groups:

- applied AI suitable for assisting select features of cognitive work (light blue)
- advanced computing and communication technologies (gold)
- robotics technologies for sensing, manipulation, moving (pink)
- human-like performance of complex collections of cognitive work (green)

The shifts seen in each forecast period are a complex aggregation of simpler job-level computation. For each job, the TPV scores are normalised to represent shares of work in the job, and these are multiplied by adoption curves for each of 42 technologies, where the curve goes from 0 at time zero to a maximum anticipated substitution at the end of the forecast window. The TAM is a matrix with a row for each task primitive and a column for each of the individual technologies; the cells contains values of 0,1, or 2 to indicate no link, some substitution, or direct applicability of each technology (column) to each task primitive (row). For each technology, we vary the maximum extent of adoption, the X-value of the curves midpoint (in terms of its maximum height), and the slope (values range from gradual to steep). For each scenario, the forecasting routine combines these inputs in a calculation that produces a schedule that shows shifts from human labor into technologies. For the visualisation, results are aggregated by subunit and technology to show a summary view. Although the visualisations we show here are static images, they are generated by an interactive tool that allows for filtering of the results by, for example, country, organizational subunit, seniority levels, individual pay bands, and subsidiary (different than functional subunit).

Figure 2 is based on the adoption curves we think are most likely; it produces a forecast in which roughly 50% of the work being done now gradually shifts to being done by new tools.

FIGURE 2: Snapshot of a 20-years forecast on the relative share of the total workforce; it shows what we believe is the most likely scenario

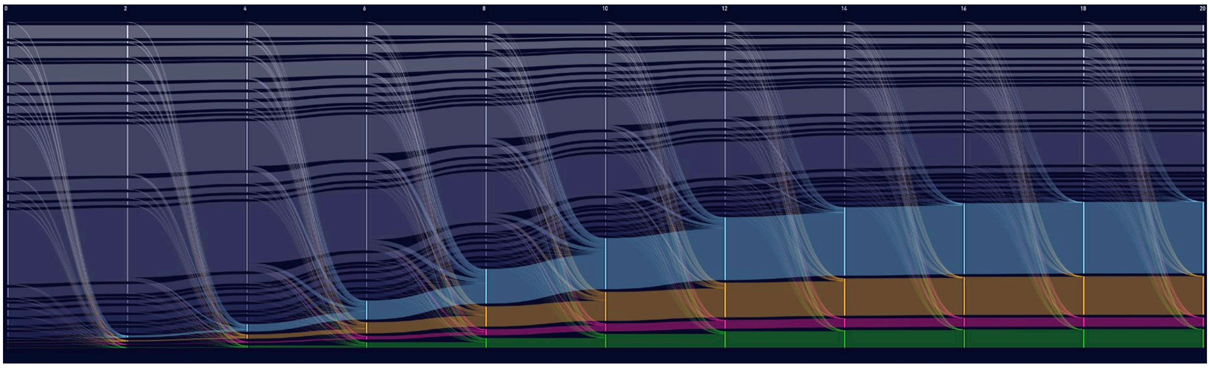
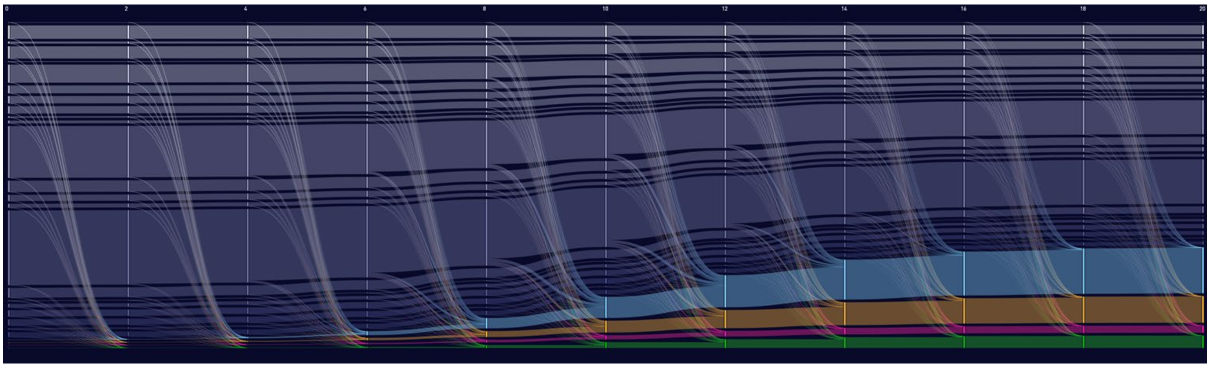


Figure 3 is based on a more pessimistic set of adoption curves consistent with pushback against technologies; for work being performed in 2020, the forecast shows a reduction of roughly 25%.

FIGURE 3: Snapshot of a 20-years forecast on the relative share of the total workforce; it shows a more pessimistic scenario



Discussion

In setting the adoption curve parameters for each scenario and comparing results across them, we were initially vexed by a surprising result: looking across the subunits, there was a surprising low variance in the percentage of work that shifts from human workers to technologies. In contrast to this, we expected to see sizable differences in impact between subunits such as finance and operations. To put that another way, we expected to more work flowing into the robotics band (pink) for subunits where there is more physical work. Although there were differences between these cases, they were much smaller than expected.

After tweaking the adoption curve parameters and the values of the TAM cells, however, results changed surprisingly little.

On closer examination, we realised each subunit is a sizeable hierarchy with employees distributed across pay bands from low to high. When comparing subunits like finance and engineering to, for example, more operationally intensive field-based work, we therefore found the differences muted by the preponderance of staff up and down the hierarchy. Looking into the contents of the jobs spanning the hierarchy from low to high, we found that very similarly worded responsibilities in jobs from very different subunits. Even though engineering managers might think of themselves as very different from managers in, say, legal, HR, or Logistics, the jobs have very similar wording of responsibilities, so the task mining analyses therefore produced very similar task primitive vectors. In turn, this leads to low between-subunit variance in predicted shifts of human labor to technologies.

During doing this work, COVID hit, and we had to stop doing regular face-to-face meetings with our research / project team (8 in all) and our collaborators at the company. Like so many are doing these days, we coped by increasingly heavy reliance on virtual meetings using Microsoft Teams.

As we did this, we adapted new strategies including always-on co-working sessions to keep each other going, much as cockroaches in the mazes of Zajonc's famed work on social facilitation (Zajonc 1965). Working our way back from these experiences to what was going on in the data, we realised we were finding ways to do what we were seeing in the data — keep ourselves sufficiently knit together that we stayed on task and continued to trust in each other's work as we collaborated.

What does this have to do with potential longer-term effects the current COVID-19 might have on work, job design, and organization structure? Sadly, our collaborators are now facing a very large reduction in the company's workforce. Although the scale and details of their planned layoffs are largely a top-down exercise designed to hit a number that seems non-negotiable if they are to survive the current downturn, the experiences of these past months have given them quiet confidence to believe they will be able to adapt to new ways of working — ways that do not require them to occupy as much office space or be in the same space together as often as they would have previously though all but essential. Both in the data and in changes we have all made to adapt team routines to COVID-19, all of us in the combined project team (spanning two organizations and multiple locations) have seen the importance of social gluing—the work we do to maintain the social cohesion needed. And as we look to work that will be done by software bot and physical robots, we speculate that those tools will need to be designed to facilitate social gluing, too—an important and challenging design problem.

References

Amador Diaz Lopez, Julio, Miguel Mollina-Solana and Mark T. Kennedy. 2018. "Foo.Castr: Visualising the Future Ai Workforce." *Big Data Analytics* 3. doi: https://doi.org/10.1186/s41044-018-0034-z.

Barney, Jay B. and Robert E. Hoskisson. 1990. "Strategic Groups: Untested Assertions and Research Proposals." *Managerial and Decision Economics* 11:187-98.

Coase, Ronald H. 1937. "The Nature of the Firm." *Econometrica*:18-33.

Davis, Gerald F., Kristina A. Diekmann and Catherine H. Tinsley. 1994. "The Decline and Fall of the Conglomerate Form in the 1980s: The Deinstitutionalization of an Organizational Form." *American Sociological Review* 59:547-70.

DiMaggio, Paul and Walter W. Powell. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields." *American Sociological Review* 48:147-60.

Ekeh, Peter P. 1974. *Social Exchange Theory: The Two Traditions*. Cambridge, MA: Harvard University Press.

Hoberg, Gerard and Gordon Phillips. 2010. "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis." *Review of Financial Studies* 23(10):3773-811.

March, James G. and Herbert Alexander Simon. 1958. *Organizations*. New York: Wiley.

Meyer, John W. and Brian Rowan. 1977. "Institutionalized Organizations: Formal Structure as Myth and Ceremony." *American Sociological Review* 83:340-63.

Modigliani, Franco and Merton H. Miller. 1958. "The Cost of Capital, Corporation Finance and the Theory of Investment." *American Economic Review* 48(3):261–97.

North, Douglass C. 1990. *Institutions: Institutional Change and Economic Performance*. Cambridge: Cambridge University Press.

Pfeffer, Jeffrey and Gerald R. Salancik. 1978. *The External Control of Organizations: A Resource Dependence Perspective*. New York: Harper & Row.

Thompson, James. 1967. *Organizations in Action*. NY: McGraw Hill.

Williamson, Oliver. 1994. "Transaction Cost Economics and Organization Theory." in *The Handbook of Economic Sociology*, edited by N. J. Smelser and R. Swedberg. Princeton, New Jersey: Princeton University Press.

Zajonc, Robert B. 1965. "Social Facilitation." *Science* 149(3):269-74.

Zuckerman, Ezra W. 1999. "The Categorical Imperative: Securities Analysts and the Illegitimacy Discount." *American Journal of Sociology* 104(5):1398-438.