The Coevolution of Tasks and Technologies

ABSTRACT

As work changes, so does technology. The two coevolve as part of a work ecosystem. This paper suggests a way of plotting this coevolution by comparing the embeddings - high dimensional vector representations - of textual descriptions of tasks, occupations and technologies. Tight coupling between tasks and technologies - measured by the distances between vectors - are shown to be associated with high task importance. Moreover, tasks that are more prototypical in an occupation are more important. These conclusions were reached through an analysis of the 2020 data release of The Occupational Information Network (O*NET) from the U.S. Department of Labor on 967 occupations and 19,533 tasks.

We investigate the work ecosystem by decomposing occupations into tasks. We introduce technology as a resource that interacts with the rest of the ecosystem, based on the concept of use plans. We examine the relationships among these entities using semantic embedding techniques and discover that internal and external tight coupling enhances task importance.

Keywords:

Work ecosystem; Future of work; Task; Technology; Occupation; Embeddings

Coevolution of Task and Technology

INTRODUCTION

Recent research in information systems and related fields has grappled with understanding how the latest wave of technologies in the areas of artificial intelligence (AI) and robotics are affecting the way we work. There is a kind of unease related to what is being discovered. It is not clear if humans in the loop steering AI is better than machines in the loop steering humans. It is not clear if and when full automation is a better economic solution, and what effects new waves of augmentation and automation are having and will have on society. Notably, recent studies have suggested that teaming humans with AI may lead to better quality outcomes, but at a cost: building the AI and its interfaces is expensive (Lebovitz, Lifshitz-Assaf, & Levina, 2021). Moreover, such systems often demand more time from humans than less, and involve humans mastering additional skills related to the technology. By contrast, some other studies have implied that we are in a transition, and that one potential destination is full automation of cognitive tasks (Cai, Winter, Steiner, Wilcox, & Terry, 2019). Studies on human-in-the-loop are being performed, the implication being it helps to have the human somewhere in the decision process — but we need to study it, because it is not always clear (Baird & Maruping, 2021; Berente, Gu, Recker, & Santhanam, 2021; Teodorescu et al., 2021; van den Broek, Sergeeva, & Huysman, 2021). Such research, when it is empirical, is taking place as field studies, spotlighting very particular contexts and seeking to understand them in depth. By contrast, this study, also interested in how work is being affected by AI and related technologies, looks across a wide range of occupations and looks for changes in the co-evolution of tasks and technologies.

Occupations can be seen as constituted by a collection of tasks: The US department of labor has encoded the tasks related to over 1000 occupations (“About O*NET,” 2019), and job ads often define the tasks to be performed (Loth et al., 2010). Some of these tasks are closer to the core identities of their occupations, while others are more peripheral. Within an occupation, certain tasks may share similarities in activities, methods, or goals, while some other tasks can be unique. Many tasks are completed by human workers with the help of computer technology. While aspects of tasks can be automated by modern technology, the degree of dependency of tasks on technology varies. Moreover, tasks and technologies co-evolve, with both affecting changes in the other. This paper starts with the conjecture that the relationships among task, occupation, and technology can provide a way to understand the evolution of occupational tasks and to improve job design. This research can be seen as a continuation of a current conversation in the management disciplines related to the future of work, including not only case based (Lebovitz et al., 2021), but also broader looks across occupations (Acemoglu & Restrepo, 2019; Bailey & Leonardi, 2015; Felten, Raj, & Seamans, 2021; Frank et al., 2019; Raj & Seamans, 2019). Distinct from this work, the approach outlined here conceptualizes a space that allows for an analysis of the similarity between technologies and tasks, a step towards being able to plot their coevolution.

In this research, we view occupation as a system and its tasks as its subsystems. We draw on theories of the compositionality of language that have led to the use of language embeddings as a way of characterizing, comparing, and combining semantic meaning (Stewart & Eliasmith, 2012). By embedding the verbal descriptions of each system and its subsystems, we calculate the similarity between them. Similarly, we calculate the similarity between task and technology descriptions, as well as the similarity among tasks within the same occupation. In this we relate the similarity of tasks and technologies to the importance of a task within an occupation.

There are strong reasons to seek to better understand occupations and their changes over time. Recent economic disruptions from a pandemic have created quandaries, as economists and policy makers seek to better understand which jobs are being lost, how compensation is changing, and why workers quit and seek different occupations. Technology has played a role in keeping companies afloat, but has also been susceptible to supply chain shortages (Sheffi, 2021). Some argue that the pandemic accelerated automation - that is, companies, not able to employ people, spent capital on productivity-enhancing tools. Economic data support such narratives, but over the last two years experts in many fields produced divergent estimates about employment numbers, occupational shifts, and wage inflation (Micheli, Johnson, & Godsell, 2021). Indeed, supply shocks tend to increase inflation, but automation tends to increase deflation, because rising productivity reduces costs. One reason for varying predictions among experts may be the tools that are available: summary statistics can show who is falling out of the workplace, but doesn't help understand the role technologies - and the designers of technologies - may play in reshaping the workplace. Moreover, technologies are multi-dimensional: popular images of robotics-based automation may occlude the also powerful forces of clerical automation, as well as more creative forms of automation such as the design of microprocessors.

Many analyses of occupations treat occupations as very different categories. Others treat occupations as splitting along a low number of dimensions: for example, as manual or as physical. In part, these treatments are the result of the methods of analysis being used. The conjecture of this work is that occupations function as a kind of ecosystem, meaning there are interrelations between occupations that are measurable, and that within occupations a set of tasks that themselves are related to each other in a measurable way. Just as the study of ecosystems has to do with mapping out geographies and changes in migration patterns, so the study of occupations might benefit from mapping the territory and examining how the overall landscape changes over time. In natural ecosystems, there are many forces at work, including climate, weather, and disease. In the occupational ecosystem, such forces also apply, but in particular the invention and diffusion of technology can have almost immediate and disruptive effects when used as part of campaigns of organizational change. Much of modern research in information systems has worked to better understand how technologies and organizations co-evolve, often through meticulous case studies with particular companies. This work, by contrast, seeks to understand this co-evolution at a higher level. The statistics to be used will span across occupations. One particular occupation, that of journalism, will be used as an illustrative example of how change is occuring.

THEORETICAL BACKGROUND

Evolution of Occupations

Occupations, are, colloquially, what people do in work settings. A perspective over a long period of time holds that humans have, for most of history, been concerned with two activities: finding food to eat and protecting against threats (Lucassen, 2021). Farming led to differentiation, and trade between growers of different foods, and specialists like potters and weavers. Specialization accelerated with the rise of cities, starting about 5000 BCE, and led to wage labor. From about 500 BCE to 1500 CE markets evolved, with money playing a prominent role. The state became a major employer. Journalism appeared in this time period, about 100 BCE. Guilds emerged: guilds were self-governing, were made up of people in similar occupations, and looked out for the interests of its members. Newspapers appeared in Germany around 1600. Starting about 1800, the industrial revolution and its related dependence on capital allowed further differentiation of skills and the emergence of what we would see as recognizable workplaces. Steam engines in transformed transportation and manufacturing, and electricity transformed communication. Chemistry and affected medicine, textiles, and agriculture. Most recently, computers and the digital revolution have transformed again most industries. Thus, seen from afar, occupations have been evolving, differentiating over time, and intertwined with advances in technology, which also can be seen as evolving (Basalla, 1988). Smith, Marx, and Schumpeter document these changes and provide alternative models for emergence of occupations and their relationship to technologies (Marx, 2018; Schumpeter, 2017; Smith, 1937).

Smith consolidated what had been learned from England's mercantile blossoming. In particular, he articulated the division of labor as a principle. On the one side of this is the capitalist's desire for productivity. On the other is the limits of a human resource. Narrow specialization allows for a worker to build a narrow but deep expertise. It is more realistic to build up skill in one area than in many. This articulated idea, in some ways the sum of learning from the guilds, would later be refined in management science by Taylor, Barnard and Simon (Barnard, 1938; Simon, 1997; Taylor, 1911). Indeed, the idea that an occupation should be bounded by what is possible for a human to master is still in place today. Marx articulated the tradeoff between capital and labor, and discussed how machines might become better choices for those wielding capital as wages go up. That is, he articulated a competition between machine and person, and pointed out the kinds of misery that automation might bring. Schumpter, by contrast, described the advantages of markets as ways of encouraging innovation through recombination. These ideas are relevant to the current project in that they suggest occupations may have a certain boundedness having to do with human capacity to accomplish tasks. This capacity, though, can be increased by machine augmentation, so that occupations can be seen as human machine hybrids, in which some tasks are performed in hybrid mode, and others may in fact be performed entirely by machines or humans (Kogan, Papanikolaou, Schmidt, & Seegmiller, 2021).

More recent texts by Piketty and Zuboff provide a modern take on shifts in power in relation to occupations and labor (Piketty, 2017; Zuboff, 2015). Less well known are gedanken experiments that contemplate accelerating full automation by raising wages, with the eventual goal being the elimination of human work and its replacement by variations of universal income (Srnicek & Williams, 2015). This kind of reverse Marxism calls for letting automation happen faster so that the work of distributing surplus can begin. But it does not confront the reality of occupations - that most are mainly accomplished by humans, and that even automated tasks have humans involved at a different level: designing, building, and maintaining the machines. Indeed, recent information systems literature finds that artificial intelligence, done well, can lead to higher quality outcomes, but is more expensive, in that both humans and machines need to work together, and the coordination costs mean that humans are actually slowed down (Lebovitz et al., 2021). This evidence suggests it is important to look at potential automation at a much more granular level to understand when augmentation provides the best quality, and the extent to which such augmentation is more or less expensive than the pure alternatives of either all human or all machine efforts, assuming the tasks can be performed in other than hybrid mode.

Malone points out that the digital once again makes possible guild-like structures (Malone, Yates, & Benjamin, 1987). Crowd work and the gig economy pose an alternative model to traditional occupations (Kittur et al., 2013). Their are other ways to look at organizations: instead of as networks, they can be viewed as fields of present and potential relations, a view of Bourdieu (Bourdieu, 1997; Cutchin, Aldrich, Bailliard, & Coppola, 2008) that has been taken up by IS scholars (Levina & Arriaga, 2014). This view is pertinent to our discussion, because it encourages a nuanced view of the role of economic capital and other forms of capital, including skills and interests, all of which arguably change the evolution of occupations.

Design of Occupations

Workers of different occupations produce work under different processes and work conditions. When designing an occupation, the overall work is often divided into smaller activities. These activities are then combined into tasks, which are further combined into jobs (Susman, 1976). Therefore, tasks, or clusters of tasks, can be seen as the subsystems of occupations.

Skills, tasks, and technologies.

Occupations can be thought of as sets of tasks. Tasks require either human skills or technologies to accomplish. Sometimes the technology fully accomplishes the task, substituting for human labor. Other times, tasks are accomplished by humans, with skills, augmented by technologies (Acemoglu & Restrepo, 2018; Frank et al., 2019; Kogan et al., 2021).

Technologies are described pragmatically in terms of what they do — their functions — and how they do it — their mechanisms (Basalla, 1988; Bunge, 1966; Garson, 2013; Hickman, 2009, 1990). In particular, there is dual nature to technical artifacts: they are physical objects, and they come out of use plans, the intention of the technology (Houkes & Vermaas, 2010; Kroes & Meijers, 2006; Pols, 2020; Vermaas & Houkes, 2006). These plans are created initially by designers, and they are implemented by users who seek to perform a particular task. In this account, the impetus for a technological development may be a task description: an engineer realizes that a particular technology can be invented or can be applied to accomplish a task, and that task then becomes a use plan that guides the design and implementation of the technology. This version of theory about function comes out of debates over the role of function in biology: it does appear that, say, a heart has function in the body, but it is less clear how the function emerges from evolution: there is no design or intention, although natural selection does perform a kind of design space exploration (Ehring, 1985). In the case of technology, there quite clearly is intention: technologies are designed to perform certain functions. But it is also clear that sometimes technologies are appropriated for functions different than those intended by designers. This is called exaptation (Andriani & Kaminska, 2021). The dual account of technology allows for an analysis of the intentions of a technology, as manifest in how the technology is described by its creator. But since a technology is an artifact with its own attributes, it is possible for users to find functions for which those attributes are useful. In the context of occupations, clearly both processes happen. Companies design technologies in order to accomplish tasks inside particular occupations. But users in different occupations may realize the technologies also apply in different occupations, and technology usage spreads, with companies eventually catching up with such user innovation, incorporating the new plans of use into future product descriptions and roadmaps.

More detailed verbal and verbal descriptions of technologies and their use plans can be enough to allow them to be replicated: patent systems around the world work in exactly this way. Patents also provide one organized way of classifying technologies, and the trees of classifications used by patents have been used to measure technological distance: the number of hops up and down the tree between two technologies can be used as a measure of distance, as can more complex ways of comparing the distributions of patent libraries (Jaffe, 1986; Yan & Luo, 2017). More recently, natural language processing techniques have been used to measure distances between technologies. For example, TFIDF schemes can be used to figure out how novel a patent is relative to former patents (Kelly, Papanikolaou, Seru, & Taddy, 2021). Most recently, word embeddings provide a way of computing vectors that allow technologies to be compared (Kogan et al., 2021). The theory underlying embeddings is the compositionality of meaning: that ideas can be built out of the aggregation of other ideas. Embeddings as vectors allow for combination through addition and convolution, and they have been argued to be biologically plausible: for example, a network of neurons can possibly encode high dimensional vector spaces that are compositional (Stewart & Eliasmith, 2012).

One unifying frame based around tasks is coordination theory, which holds that interdependent tasks may require resources, and may be accomplished by actors, including both humans and machines (Malone & Crowston, 1990). This view can utilize technologies as resources or as actors, both at the service of completing a set of tasks.

Modular Systems Theory

Modularity is a systems concept that describes “the degree to which a system's components can be separated and re-combined, and it refers both to the tightness of coupling between components and the degree to which the ‘rules’ of the system architecture enable (or prohibit) the mixing and matching of components (Schilling, 2000).” This concept appears in different forms in theories of ecological complexity (Allen & Starr, 1982) and collective intelligence (Malone & Bernstein, 2015; Page, 2007). In the context of occupation, its tasks and technology, we can examine the tightness of coupling by computing the distances between the descriptions of these entities.

THEORY DEVELOPMENT

Conceptualizing Task Importance in Occupations

Occupations are made from tasks. Of late, economic scholars have argued that we need to do better analysis at the task level (Acemoglu & Restrepo, 2019). The collection of panel data about tasks from recent employees asks workers not only about the tasks that they work, but also about the importance of the tasks that they work on. This importance of a task may give insight into changes in occupations, as it is reasonable to ask if it is the more important or less important tasks that receive attention from companies that seek to automate part of a profession. It is also reasonable to ask if rising or falling levels of importance are harbingers for larger shifts in an occupation, the largest shifts being splits and mergers. As a precursor to later analysis, we show how task importance can be visualized with respect to descriptions of occupation and technology.

Visualizing Task Importance

Figure 1 shows tasks from two occupations plotted in two ways. The first one (left) by reducing the 512 dimensional embedding space of each description to two dimensional space using principal component analysis (PCA). The other one (right) is to plot the tasks by its distances to the descriptions of the occupation and technology computed from the embeddings of the texts. Note that the PCA plots may not reflect the distances accurately due to information lost during dimension reduction.

Insert Figure 1 about here

The round dots represent tasks. The color of each dot represents the importance rating of that task, with red being the most important and blue being the least important. The black diamonds represent the description of the occupation while the black star represents the description of technology commodities of the occupation.

Conceptualizing distances between tasks, occupations and technologies

Occupations are descriptions at a high level of what people do at work. They reflect the forces of specialization in an economy, in which it generally makes sense for people to become increasingly effective at a subset of tasks over time, rather than to spread their learning time across all tasks necessary for the functioning of an institution. The occupation is a collection of tasks; the number of tasks will vary, but there is a sense of optimality: too many tasks may make it impossible to acquire expertise, and too few tasks may create problems of integration, because the output of one worker is likely to be input to another worker, and managing long chains is harder than managing short chains. Moreover, employees are hired into occupations: too many tasks may create unrealistic demands on training. For example, it is not realistic to expect that doctors master all of law, or lawyers all of medicine: the training costs are just too high for individuals and for institutions. That is, the number of tasks in an occupation is likely bounded, and the bounds might consider a combination of the amount of time the task takes to perform, the amount of time to become trained on a task, and the relation of the task to other tasks. If tasks are similar to each other, then acquired expertise in one might reasonably translate to another. But for some tasks such a translation is not likely: for example, a geographic engineer working for a railroad may engage in tasks related to evaluating aerial data of train tracks, but may also engage in tasks related to the inspection of rails in the field. The latter may call for knowledge of a set of safety protocols unrelated to training in imagery and geography. This sense that tasks may have similarity to each other is behind our general conjecture that the structure of this similarity, the network of tasks, may lend insight into occupations. To extend the example, the geographic engineer when performing office tasks may utilize geographic software tools, whose descriptions are likely to closely match task descriptions: for example, analyzing for wear the intersections of rails and roads from aerial photographs. Whereas the tasks related to on-site inspections may use very different technologies, such as lasers used to measure road grades.

That is, conceptually, some tasks may have differing distances to other tasks, measured through the dissimilarity of the verbal descriptions of tasks. Likewise, tasks may have differing distances to technologies that might conceivably be mustered to assist in performing the task. The supposition is that technologies that are very similar in description to a task might be utilized to augment the human worker in performing the task. This might result in better quality outcomes, or may reduce the amount of time spent on the task, or both. All tasks, though, are not equally weighted. Some are more important for the occupation. This might be measured by some measure of centrality based on description. Or this might be measured through asking workers about their perception of task importance.

Occupations and Tasks: Centrality as importance

What tasks are considered the most important? One way to think about this is through the lens of centrality. That is, more important tasks are more likely to be close to all other tasks. This conjecture is consistent with the concept of distance in clusters (Kaplan, 2004).

Specifically, the *internal task distance* is the average distance between the task and the rest of the tasks within the same occupation. The longer the distance is, the less similarity the task shares with the rest of the tasks in the occupation. This leads to the following hypothesis:

Hypothesis 1. Shorter internal task distance increases task importance.

Occupations and Tasks: Prototypicality as importance

Another way to think about importance is in terms of prototypicality. That is, a prototypical task is one whose description is closest to the description of the occupation. This more prototypical task can be considered to represent the occupation, and, as a result, is likely to be considered more important, consistent with the understanding built in psychology of the importance of prototypes in concept formation (Cohen & Murphy, 1984). *Task prototypicality* is the distance between the task and the occupation, as measured by the distance between the embeddings of the task description and the embeddings of the occupation description.

Hypothesis 2. Higher task prototypicality increases task importance.

Tasks and Technologies: Proximity as importance

It may be that the importance of a task is positively related to its proximity to technology. This might happen for two different reasons. In the first, a company seeking to find a market for a technology tailors that technology to accomplish a task deemed important by those in the occupation. In the second, given a technology is present that makes a task easier to accomplish, that task can be accomplished in a very productive way, making it important for the productivity of the occupation. Both of these uses are supported by conceptualizations of technology that allow for both the intention of a designer in creating an artifact for a particular task, and the intention of a user who discovers a task for which a technology is suitable (Andriani & Kaminska, 2021; Vermaas & Houkes, 2006). On the other hand, it may be that task with a related technology that automates the task makes that task less important in the occupation: it is just assumed that work will happen, and it recedes in importance because little skill needs to be built nor much effort expended.

Technology is seen as a resource in models of coordination, and so resource proximity is measured by the distance between the description of the task and the description of the technology commodities used by the occupation to which the task belongs. Again, smaller distance between the two entities indicate closer resource proximity. While it is unclear a priori which way close resource distance will affect technology, there is some evidence that technology developers focus on providing solutions to important tasks in an occupation (Bessen, 2016; Willis, Duckworth, Coulter, Meyer, & Osborne, 2020), which leads to:

Hypothesis 3. Closer resource distance indicates higher task importance.

METHODOLOGY

Data

We analyze several datasets released by the Department of Labor in the form of the O*NET database, as this data reflects practice in the US economy. The datasets are collected through surveying job incumbents and experts using standardized questionnaires ("About O*NET," 2019). The key datasets for this study include Task Ratings, Technology Skills, and Occupation Data. The Task Ratings dataset contains descriptions and ratings on the relevance, importance, and frequency of the tasks associated with each occupation. We use the importance rating, which ranges from 1 to 5 with 5 being the most important, as our dependent variable. There are in total 19,533 tasks with importance ratings from 967 occupations. The Technology Skills dataset provides information about software commodities used by each occupation. There are 127 commodities mentioned in this dataset with specific software package examples. However, the dataset doesn't include descriptions for the commodities. We search online resources and compile textual descriptions of these technologies. The Occupation Data dataset provides descriptions of each occupation.

Construct Measures

We measure the coupling effect, a crucial concept in modular theories, of a task and another system by the semantic distances between the description of the task and the description of the other systems. The semantic distance of two sentences can be computed with the embeddings of the texts. We embed the textual descriptions of all tasks, technology commodities and occupations with pre-trained models from the universal sentence encoder (Cer et al., 2018). Then we calculate the distances using the embeddings. The greater the distance is, the less similar a task is from the other entity, which in turn means the task is more loosely coupled with the other entity.

RESULTS

We test our hypothesis with ordinary least squares regression models. We select two sets of control variables: the embeddings of the task description, and the importance ratings of 52 abilities of the occupation to which the task belongs. Because the control variables have high numbers of features (512 for the embeddings and 52 for the abilities) that are not of our main interest, we omit detailed results for them and only include constants in the first two models. We report the results of the regression models in Table 1.

Insert Table 1 about here

As we can see in the table, after adding the three key distance measures to the control variables as independent variables, the r-squared value increased from 0.29 to 0.33. We can also see that all three key distance measurements have negative effects on the skill importance rating of a task, which support our hypotheses that shorter distances indicate higher skill importance ratings. Figure 2 illustrates the relationships between the variables and the regression results. The first two key distance measurements — the internal task distance and the task occupation distance — are positively correlated, which is to say when the embeddings of a task is closer to the average of the embeddings of the rest of the tasks in the same occupations, it is also more likely to be closer to the description of the occupation it belongs to.

Insert Figure 2 about here

While there are negative correlations between the three key distances and the task importance ratings, the directions of these effects aren't clear. In fact, we believe it is a two-way street when it comes to the relationship between task importance and technology resources. That is to say, on one hand, tasks that are closer to the technology resources tend to be more important; on the other hand, technological functions that help complete the important tasks are more likely to be developed and deployed.

To discuss how the results can help us understand the coevolution of tasks and technologies, we should first discuss what it means for the description of a task to have a long/short distance to the description of technologies. When the embeddings of a task statement has a long distance to the embeddings of the description of a certain technology or the combination of multiple technologies, it indicates that the functions of the task and the technologies are dissimilar. More specifically, it could mean that within this occupation, there are no technologies aiming to do what the task is set out to achieve, either due to the nature of the task being highly human centered and nontechnical (involving mostly human skills), or due to relevant technologies not fully evolved and widely adapted by the occupation. In addition, we also noticed that general tasks that are high-level and less descriptive tend to have longer distances to technologies. On the other hand, a shorter distance between tasks and technologies could indicate similarities in functions.

The negative correlation between task importance and technology distance from the regression result represents the overall trends of the coevolution of tasks and technologies, which provide insights in the following way: when important tasks have long distances with technologies, it may be an indicator for potential new technologies to be introduced and reinvented so the distances can be shortened. On the other hand, when important tasks have relatively short distances to technologies, we should pay attention to the specific technologies that they are close to and make it even more efficient by tailoring their functions to the occupation's needs. Meanwhile, as technologies are being developed and adapted, the way tasks are described and organized may also change. One potential way this change may happen is that general tasks that have long distances to technologies may be broken down to smaller, more specific tasks that are closer to technologies. Tasks that used to be described by their functions may be described by the technologies being predominantly used.

It is worth mentioning that embeddings are complex artifacts, based on expensive-to-compute foundation models (Bommasani et al., 2021). These models and their applications are very much an active area of research (Păiș & Mitrofan, 2021; Singhal, Liu, Blessing, & Lim, 2021). Textual similarity computed using embeddings, while arguably better than previous natural language processing techniques including TF-IDF, latent semantic modeling, and topic modeling, don't always match human perceptions of similarity (Jain, Kalo, Balke, & Krestel, 2021; Lastra-Díaz et al., 2021). In this application, the results rely on the descriptions of the tasks and technologies. In some circumstances, embeddings may emphasize certain vocabularies and thereby misinterpret the meaning of the full sentences.

To better understand the implications of the results, and to guard against measurement error introduced by embedding-based similarity calculations, we take a closer look at two occupations as examples — *Reporters and Correspondents*, and *Geospatial Information Scientists and Technologists*. We focus on highly important tasks — those with importance ratings of 4.0 and above.

For the occupation of *Reporters and Correspondents*, the relationship between technology distances and task importances isn't what we expected from the overall regression result. In fact, there is a slight positive correlation between task importances and technology distances (Figure 3).

Insert Figure 3 about here

We learn from the regression results that task importances and technology distances are negatively associated over all data points, but we also see exceptions and discrepancies in individual cases like this. This is because each occupation has a much smaller sample size in tasks compared to all occupations combined, therefore the trend may not be obvious or may even be different. The characteristics of the technologies associated with the occupation of interest may also vary. Which is to say the kind of technology commodities and the language used to describe them can affect the embeddings, and therefore the distances.

To get a better idea of the relationship between task importance and technology distance within this specific occupation, we separate each technology commodity from the overall technology description and measure the individual distances between tasks and each technology commodity. We then look for strong negative correlations between task importances and the individual technology distances. We find two key technologies that have moderate to strong negative correlations to task importance ratings. One is information retrieval or search software, which has a correlation coefficient of -0.41, and the other is map creation software with a correlation coefficient of -0.55. The example software packages for these technology commodities are LexisNexis and ESRI ArcView, respectively.

The information retrieval or search software is more straightforward in this example: extracting information from a large amount of data is one of the most important aspects of a reporter's job. However, the strong relationship between a reporter's tasks and map creation software is not as intuitive. Therefore, we dive deeper into specific task descriptions that have relatively close distances to the description of map creation software (Table 2).

Insert Table 2 about here

While there's no direct language in the task descriptions that clearly state the functions of map creation software, the idea of researching and describing background information, when embedded, share a certain level of similarity to the embeddings of the software description, which states "A geographic information system (GIS) is a conceptualized framework that provides the ability to capture and analyze spatial and geographic data. GIS applications (or GIS apps) are computer-based tools that allow the user to create interactive queries (user-created searches), store and edit spatial and non-spatial data, analyze spatial information output, and visually share the results of these operations by presenting them as maps."

The dataset doesn't explicitly connect technologies to tasks but it is highly possible that GIS applications are being utilized to achieve these tasks. We uncover this connection by taking advantage of information embedded in high dimensional space that is not obvious from the text level. Indeed, GIS is actively used in journalism (Herzog, 2003; Molina Rodríguez-Navas, Muñoz Lalinde, & Medranda Morales, 2021; Wasike, 2005). This method could draw attention to specific technology skills that are often overlooked for certain occupations.

Examining individual technology in addition to the combined description of all technologies also provide insights on how technology may evolve within an occupation. By comparing high importance tasks and their distances to different technologies, we notice three major categories of tasks: 1) tasks with close distances to individual and combined technologies used within the occupations; 2) tasks with far distances to combined technologies within the occupations but close distances to individual technologies within and outside the occupation; 3) tasks with far distances to combined technologies within the occupations but close distances to individual technologies outside the occupation. Examples of the three categories can be found in Table 3.

Insert Table 3 about here

CONJECTURES

The results of this study answer some questions and create others. In particular, the detailed look at particular technologies in two different occupations suggest new theoretical ideas, which form here as conjectures that future research might further refine and test. Specifically, each category — enumerated above and shown in Table 3 — has different implications about how technologies may evolve over time. Category 1 tasks work well with the current combination of technologies and fit the overall trend from the regression results. They also have specific technologies that serve similar functions. It's likely that these specific technologies and the skills associated with them will become more important for the occupation. It is also likely that more efficient applications within these technologies will be developed to help achieve better results for these tasks.

Category 2 tasks are close to some of the technologies that are available but could benefit if new technologies were introduced to the occupation. Due to its high importance and technical nature, the closeness to not yet widely adapted technologies may motivate new technology skill combinations and new applications being developed. Technologies typically used in another occupation may be reinvented to have different functions so that they can assist different occupations.

Category 3 tasks require some out of the box thinking because they don't share much similarity with current available technologies within the occupation. Therefore, searching outside the occupation and identifying key technologies that serve similar functions from a linguistic level could indicate possible directions for future technology usage and development.

As technologies are being drawn closer to important tasks and new functions being developed to meet the needs of these tasks, tasks also transform and evolve. First, new tasks that require more sophisticated or even new technology skills may emerge. For example, as information retrieval software becomes more important and new applications being diffused into the journalism profession, tasks with descriptions that emphasize certain software packages or technology skills may be added. Eventually a new occupation may emerge due to increasing demand and specialization of certain technologies. For example, the occupation *Data Journalist* has been appearing in job ads in recent years.

Meanwhile, existing tasks may be described differently as they incorporate new technologies and adopt new processes. Over time, certain aspects of an occupation may become closer to parts of other occupations, which could lead to occupation split or merger. For example, the occupation *Broadcast News Analysts* and the occupation *Reporters and Correspondents* merged into one after a taxonomy update in O*NET: *News Analysts, Reporters and Journalists*. One potential reason for this merge may be that the technology applications used for some of the tasks in both occupations are similar therefore require the same skill sets and can be done by the same professionals.

Lastly we noticed that the language of some tasks are more abstract. They describe a general goal instead giving specific steps or procedures. Often we find these abstract tasks have longer distances to technologies. However, as technologies automate or augment aspects of these tasks, they may be broken down into more specifc, lower-level tasks. For example, the task “Report on specialized fields such as medicine, green technology, environmental issues, science, politics, sports, arts, consumer affairs, business, religion, crime, or education” doesn’t specify what activities are involved in these reportings. But if there are data analysis software applications developed specifically for investigative research on specialized fields, application specific language may be used to describe part of the task.

The coevolution of task and technology won’t stop after one cycle. As technologies develop new functions and being deployed in new occupations, the descriptions of them may change, which in turn change the distances between them and the tasks. The distance changes may drive more technological advancement and adaptation, which could lead to tasks being articulated in different ways and occupation reorganizations.

While the high task importance could be a driving force for technology evolution as important tasks tend to attract more and better technology applications that have similar functions, there are other factors at play as well. The rate and direction of evolution may also be affected by the skills associated with the tasks and the amount of additional skills required by the technologies. These other factors should not be neglected when studying the entire ecosystem although this study focuses mainly on the distances between technologies and tasks.

In summary, the observations of specific occupations led to the following conjectures.

Exaptation: When an important task is far from technologies that are currently being used in its occupation, there's a potential opportunity for technologies that exist in other domains to be redesigned so they can serve this task's functions.

Emergence: New tasks and eventually new occupations may emerge when exaptation happens.

Task Evolution: Tasks evolve as technologies change. Tasks with abstract descriptions and longer distances to technologies may be decomposed into more specific tasks as technology advances.

[more discussion of these conjectures and how they might be tested]

CONCLUSIONS

Job design is a process that concerns how activities are grouped into tasks and tasks into jobs, as well as one that maximizes the capability and productivity of a group of workers in certain sociotechnical environments. The importance of a task and the usage of technology commodities within an occupation reflect the collective decisions and experiences of the job experts and worker groups. Descriptions of tasks and technologies adopted by an occupation adjust to each other: more technology commodities are created around the important tasks, and tasks are designed taking into account the technological tools available. Therefore, understanding the dynamics between these entities can provide signals to guide the economy through design decisions for occupational tasks and technologies. For example, as smarter machines become more common in the workplaces, new tasks may emerge and new skills will be needed.

The results of this study show that tight coupling relationships, internal or external, enhances task importance. This finding is particularly interesting when it comes to the relationship between task and technology. While many people believe that technology, especially automation and artificial intelligence is replacing human labor, what we discover here indicates that tasks that share greater similarity with technology are likely to be considered more important by the human workers. This means that how a task is completed may be different when modern technology is being introduced, but that the work itself and the human intelligence involved is not disappearing. This result is related to work that has found that the introduction of artificial intelligence often increases quality, but also increases time spent on task (Lebovitz et al., 2021). This leads to a potential conjecture related to the development of artificial intelligence: that its development is often towards tasks that are important in an occupation, and that its development further increases the importance of those tasks. While the target of the technological development might ostensibly be an increase in productivity, an alternative and still desirable outcome is an increase in quality. That is, much as crowds may produce high quality outcomes as a result of a canceling out of errors (Hong & Page, 2001), humans and AI together may also help cancel out each other's errors, resulting in higher quality outcomes. There may be a tradeoff, in that humans need to spend more, not less time on such tasks. But given the tasks that are being instrumented are important for the occupation, the increase in time may be warranted. This conjecture is by no means the only possible conjecture that can follow from this study. A less human-centric view is that these increases in human participation on tasks central to an occupation are a temporary step on the way to full automation: AI needs experts to help the AI with a kind of active learning, in which complex edge conditions are explored jointly, leading eventually to improvements in algorithms that will allow full automation. Humans train the AI, and, in order to get the AI to a sufficiently advanced stage, very expert humans need to be engaged until the machines crack the code. Something analogous happened in the evolution of crowd-based games related to proteins: whereas originally humans were much better than algorithms, humans eventually helped write scripts that then were used to help train algorithms (Cooper et al., 2010; Panou & Reczko, 2020).

However, protein folding games are quite different than medical diagnoses, where one might expect that humans in the loop will continue to provide value. And both situations are different than automated driving systems, where the sheer openness of the road system, its related high combinatorics, which includes the psychology of driving, challenges the predictive capabilities of machines.

Indeed, the variations in automatible work bring us back to some of the thornier issues in the study of information systems. At one pole of possible theories are those inspired by classic economics. Individuals operate in their self-interest (Smelser & Swedberg, 2010), which makes for a set of predictable choices that optimize for transactions related to education, training, and career choice. This principle of self-interest is assumed to be universal, and should apply across the entire spectrum of occupations. At the other pole of theories are those that are situated, in which each occupation might have its own field, its own institutional logic, so that generalizations across occupations will miss the situations (Bourdieu, 1990; Suchman, 1987). This study suggests that, if the strong tribal nature of these academic disciplines can be overcome, there may be intermediate theories. These theories might posit differences in occupations, but might conjecture they are commensurable, meaning that it may be possible to reason not just about one occupation but about sets, the same way that within occupations we can reason about not just one task but sets of tasks.

One of the attractions of social theories that involve fields — starting with Lewin (Lewin, 1951), and encompassing Bourdieu (Bourdieu, 1993) — is that they allow us to imagine potentials. These theories tend to work deep, examining within a field. To use a biological analogy, the way to be able to work across fields, or, in this case, across occupations, may be to use concepts borrowed from ecology, in which there are many levels of hierarchical structure, not just institution and individual. Each level has a mechanism and a purpose. The purpose itself is a mechanism that has a higher purpose. This kind of holon, this Janus of hierarchy (Allen & Starr, 1982), allows for local focus and differentiation within occupations, but also allows for a look across occupations, which split and merge as the tasks within them shift, a result of changing human needs and with that changing human-designed technologies. If this is true, then future research may expand our unit of analysis up to the occupation level and discover how the modularity of sets of occupations affects different aspects of the ecosystem of work, workers and technology. The ecosystem, like any ecosystem, has many levels. Tasks may cluster into sets of tasks, which then constitute occupations, which might cluster into sets of related occupations, that in turn form work ecosystems, that are embedded in steps to the economy, society, and the natural world, the last being the inspiration of the original concept of ecology.

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TABLE 1

Regression Model Results

Predictors	**Model 1: Controls (Task embeddings)**		**Model 2: Controls (Task embeddings and Abilities)**		**Model 3: Main effects**	
Constant	3.85***	(0.03)	3.32***	(0.09)	6.06***	(0.35)
Internal task distance					-1.06***	(0.07)
Task prototypicality					-0.50***	(0.03)
Resource distance					-0.62**	(0.23)
R-squared	0.27		0.29		0.33	

All independent variables are distance measures.
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$

TABLE 2

Tasks Close to Map Creation Software

Task Description	Task Importance	Distance
Gather information about events through research, interviews, experience, or attendance at political, news, sports, artistic, social, or other functions.	4.32	1.33
Report news stories for publication or broadcast, describing the background and details of events.	4.33	1.32
Research a story's background information to provide complete and accurate information.	4.62	1.28

TABLE 3

Task Categories by Technology Distances

Category	Task Description	Distance to Combined Technologies	Close Technology within Occupation	Close Technology outside Occupation
1	Review and evaluate notes taken about news events to isolate pertinent facts and details.	1.38	Information retrieval or search software (1.29)	
2	Gather information about events through research, interviews, experience, or attendance at political, news, sports, artistic, social, or other functions.	1.42	Analytical or scientific software (1.28)	Sales and marketing software (1.28)
3	Establish and maintain relationships with individuals who are credible sources of	1.43		Video conferencing software (1.24)

	information.			

FIGURE 1

Dimension Reduction and Distance Plot Examples

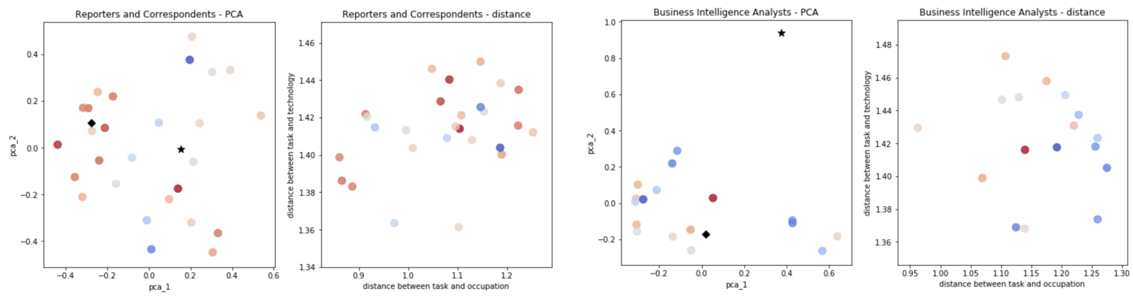

FIGURE 2

Visualizing Variables and Regression Results

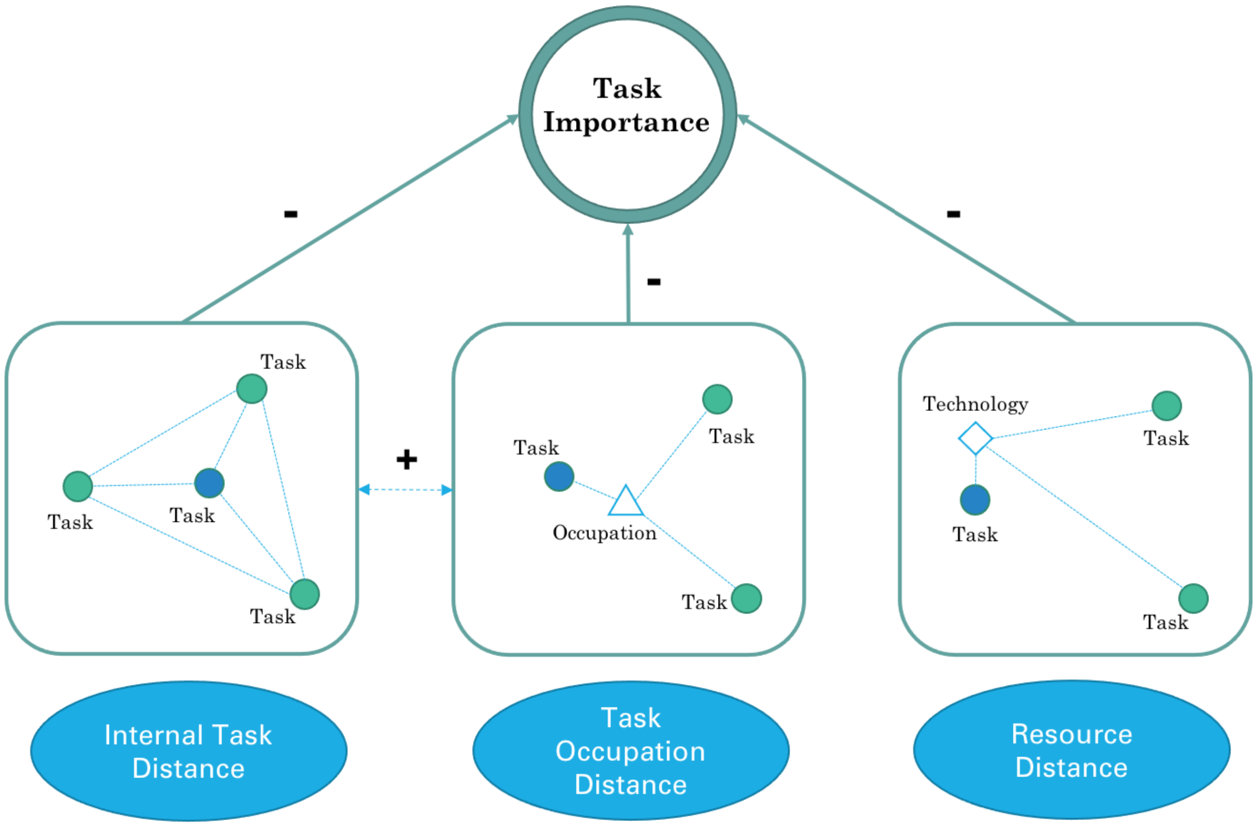

FIGURE 3

Technology Distance and Task Importance