Occupation Modularity and the Work Ecosystem

Completed Research Paper

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Abstract

Occupations, like many other social systems, are hierarchical. They evolve with other elements within the work ecosystem including technology and skills. This paper investigates the relationships among these elements using an approach that combines network theory and modular systems theory. A new method of using work related data to build occupation networks and theorize occupation evolution is proposed. Using this technique, structural properties of occupations are discovered by way of community detection on a knowledge network built from labor statistics, based on more than 900 occupations and 18,000 tasks. The occupation networks are compared across the work ecosystem as well as over time to understand the interdependencies between task components and the coevolution of occupation, tasks, technology, and skills. In addition, a set of conjectures are articulated based on the observations made from occupation structure comparison and change over time.

Keywords: Future of work, Occupation, Network, Community detection, Modularity, Work ecosystem, Evolution

Introduction

Work is an activity that happens within a complex social system. Occupations are constituted by a collection of tasks. Each task requires certain skills and abilities from workers or teams of workers and machines. Therefore, we can see the modern workplace as a multi-level, hierarchical ecosystem (Wang 2021), consisting of systems that can be decomposed into lower level components. These same systems are components in their higher level context.

The systems and their context coevolve: socio-technical developments affect the context of occupations (Adler 1992; Bailey and Leonardi 2015). It is understood that routines can be split and recombined (Cohendet and Simon 2016); perhaps at a higher level occupations also split up, combine or emerge in order to adapt and in turn further change the context; similarly, perhaps tasks are reorganized when occupations change, and perhaps the emergence of clusters of tasks presages shifts in the nature of work. The coevolution could also happen at different levels: when technology advancements change the combination of skills and abilities required for certain tasks, the occupations related to these tasks may be affected as well.

Modularity theories focus on the interdependencies of subsystems within complex systems like these (Baldwin 2019; Schilling 2000; Wang 2021). These theories can help us understand the complex relationships among elements in the work ecosystem. Consistent with past literature, we define modularity as the extent to which components can be separated from the system they are contained in. Modularity in this view is the inverse of integration, which expresses the degree of dependency of a component. Depending on the structure of the task components, an occupation can be seen as modular, integrated or somewhere in between. Modular occupations are those consisting of independent task components that share few connections, while integrated occupations have interlinked task components that are difficult to decompose.

As a step toward a better understanding of the evolution of occupations, this paper uses recent network-related techniques as a way of understanding the structure of occupations. Specifically, this paper uses data from the United States Department of Labor statistics as the basis for constructing occupation networks that can be traversed to detect clusters of tightly connected tasks — task components — based on skills and ability requirements. These components provide a measure of the modularity of occupations, and also supply building blocks for the evolution of the work ecosystem.

We posit that the work ecosystem cannot be fully understood by focusing on any single elements in isolation. While there are complex theories and tools in economics and sociology to study the future of work, there is a need to develop a deeper understanding of how different employment-related elements — skills, tasks, and technologies — interact with each other as a system.

We draw on the ecosystem perspective of Wang (2021), which provides a way of thinking about the relationships between parts and the systems they belong to, as well as interdependencies among multi-level systems. Our study is also in line with theoretical development in recent IS studies that emphasizes actions in process and routine changes rather than actors (Mousavi Baygi et al. 2021; Pentland et al. 2020; Swanson 2019). Swanson (2019) pointed out that it is crucial to understand the relationship between new technology and routines in order to gain perspective and new understanding of how technology changes. Pentland et al. (2020) used simulation to model the drifting nature of phase changes in digitized processes. By contrast, this paper also considers processes, but at a different level, considering how occupations shift over time. Building on these theories, our study seeks a new way to conceptualize, measure, and predict changes in the context of work.

In our study, we are able to discover task components within each occupation that capture structural properties like modularity. We present the partitions of task components of two occupations as examples — Data Scientists and Remote Sensing Technicians — to illustrate how our technique discovers structural and complexity differences between occupations. We find that the Data Scientists occupation is more integrated, exhibiting low modularity, while the Remote Sensing Technicians occupation is more modular, exhibiting high modularity. We then compare the similarities of these components internally and externally to understand what skills are driving the partitions and how occupations evolve over time.

Studying occupations from a network perspective and incorporating modular systems concepts and terminology has theoretical and practical significance. Recent studies of the digital and socio-technological transformation encourage a shift from actor-centric orientations toward a flow-oriented approach (Mousavi Baygi et al. 2021). Work processes and routines are organized around tasks. Tasks form occupations. Therefore, by looking at task components and structures, as well as their changes over time, we can gain insights about the flow of continuous transformation in the workplace.

In addition, we show how tasks can be associated with skills and abilities in a quantitative manner. Skills and abilities have been extensively studied in the future of work literature. Advances in AI technology, such as translation, image recognition, are associated with occupational abilities (Felten et al. 2019). This can sometimes lead to a reduction in occupational content of skills that compete with machines and an increase in skills that complement machines (MacCrory et al. 2014). These studies suggest the importance of studying technology in relation to information about human capabilities. Using this information to build occupation networks, it is possible to simulate changes in skills and abilities, which lead to changes in task components and occupation structures.

Moreover, networks have often been used for prediction purposes because they have embedded structural information (Grover and Leskovec 2016; Tan et al. 2014; Valverde-Rebaza and de Andrade Lopes 2012). In recent years, network-based machine learning models have been used to enable discovery of scientific inventions as well as innovative solutions to complex problems (Sourati and Evans 2021). Hypergraph frameworks have been proposed to capture the complexity of science (Shi et al. 2015). That is, a random walk model on the hypergraph can be used to predict how science evolves. Our study provides a way to study and predict occupations evolution in a similar manner by using rich structural information to understand the relationships among different components and using data-driven machine learning models to predict future changes in the work ecosystem. For example, it is possible to generate new tasks or occupations using deepwalk (Perozzi et al. 2014), a machine learning technique that learns representations of vertices in a network.

This paper can be considered a method and theory building paper: the concepts and techniques are described, an example of its application is shown, and, using the results of this illustrative study, we articulate conjectures related to the relationships between technologies, tasks, and occupations. Through this study, we explain how new occupations emerge from recombining task components from existing occupations; how occupations split up or merge due to technological development and skill demand changes. We also discuss how occupation modularity can benefit future studies of technology and work.

This study contributes to the Information Systems community by developing a method to analyze occupations as configurations of task components, which provides a new way of looking at occupations as socio-technical systems that evolve and change with their components. The focus is on the shared skills and abilities associated with task components within and between occupations. The paper also contributes by forming a theory that draws from both a network perspective and a modular systems perspective. This combination can potentially provide a pathway to future generative research using techniques and tools that are related to both theoretical origins.

Theoretical Background

The future of work has been discussed generally in the disciplines of economics, sociology and business (Abbott 1993; Fitzgerald 2006; Volti 2011). More specifically, the impacts of technology on work have been studied within certain occupations, organizations, industries, and across the job market in terms of process and skill requirement changes (Bartel et al. 2007; Brynjolfsson and McAfee 2012; Cai et al. 2019; Deming and Kahn 2018; Goldfarb et al. 2020). By contrast to those studies, this study focuses on studying occupations from a network perspective, viewing the work environment as an ecosystem.

Occupations as collections of tasks

Autor et al. (2003) discussed how the computerization of the workplace changes job content and in turn human skill demands by "conceptualizing and measuring job skill demands in terms of job tasks rather than the educational credentials of workers performing those tasks". In their framework, tasks were categorized into four aspects: routine, nonroutine, manual, and cognitive. The authors argued that computerization is associated with declining relative industry demand for routine manual and cognitive tasks and increased relative demand for non-routine cognitive tasks.

This framework was further explained and developed in a later paper: "A task is a unit of work activity that produces output. A skill is a worker's stock of capabilities for performing various tasks. Workers apply their skills to tasks in exchange for wages" (Autor 2013). This is further articulated in Autor and Handel (2013).

There is a rich tradition of considering tasks as an important unit of analysis inside a business: "productivity of the knowledge worker will almost always require that the work itself be restructured and be made part of a system" (Drucker 1999). As the center of work shifts from manual work to knowledge work, the focus of control should shift over to the work process in order to make work productive (Nickols 2000).

Work tasks are sometimes studied as processes, defined by Davenport (1993) as "structured, measured set of work activities designed to produce a specific output". He also pointed out that information technology is both an enabler and an implementer of process change (Davenport 1993). His work and the work of others have been used to re-engineer companies. These efforts are targeted toward increasing productivity. Single-minded approaches to achieving productivity are not always good for workers, as sociotechnical scholars have argued (Trist 1981). Action theory can be used as a guide to design and redesign work as it emphasizes both efficiency and humanization (Hacker 2003). More specifically, sequentially and hierarchically completed tasks, which are tasks that involve cognitive operations and intellectual control processes, can offer learning opportunities much greater than routine tasks that encourage downskilling in the workforce. More modern critiques of the drive toward productivity have focused on the commodification of consumer behavior (Zuboff 2019). With respect to epistemology, this paper is rooted in an ecological perspective that emphasizes relations between tasks, humans, machines, and the higher level concept of an occupation. This kind of relational view has been recently used to analyze technology (Kyriakou et al. forthcoming). The approach is quantitative and the underlying epistemology of the study is pragmatic realism, in the sense of positing an external reality concerning work that can be detected by collecting data (Skagestad 1981). We note that the graph analysis performed allows for a nuanced analysis of work contexts that can inform qualitative observational studies of current work environments, as well as generative design studies that seek to create new work environments through the design of new tasks and technologies.

In summary, this previous literature suggests that analyzing tasks is a way to gain insight into businesses. This study is in the tradition of studies that focus on tasks. It goes further than the previous literature in several ways. It explicitly models occupations as collections of tasks. These tasks themselves are related to technologies. These relations are defined as graph structures, which allow for a quantitative way of looking holistically at occupations and their evolution.

Network Community Detection

What are the advantages of a network approach to labor-related data? Networks have information embedded in them. There are ways to take this high dimensional information and compress it so that it is useful for understanding entities and their connections. One common property of many networks is community structure. In recent years, a wide variety of community detection algorithms have been developed to identify groups of interacting components in a network depending upon their structural properties (Yang et al. 2013). Identifying components brings us one step further towards understanding network structures (Newman and Girvan 2004). This kind of analysis has been applied to problems such as social media analysis (Papadopoulos et al. 2012). But not, to our knowledge, detecting task components in occupations, or understanding occupation structures and evolutionary paths.

One category of community detection algorithms focuses on optimizing network modularity (Newman 2006). It has been successfully used to find components and capture the structure of sets of components (Newman and Girvan 2004). In this study, we use the Louvain algorithm proposed by Blondel et al. (2008), which is a modularity-based heuristic greedy optimization method for community detection. We do so because the Louvain method outperforms many similar modularity optimization methods in both the resulting modularity value and the speed — the two measures of importance when comparing modularity optimization methods (Aynaud et al. 2013).

Studying occupations from a network perspective becomes possible due to the proliferation of a variety of data sources related to labor and work, including online job ads, as well as government data. These data sources can be used to create knowledge graphs (Noy et al. 2019) and networks that reflect characteristics and structures of occupations. Knowledge graphs are useful from a theoretical perspective because they allow for techniques that postulate diffusion and integration of ideas through events that bridge adjoining nodes in the graph (Shi et al. 2015), in a process akin to the diffusion and integration ideas through the interaction of people and ideas at conferences and in the workplace.

Modular Systems Theory

Why do we want to find the components of occupations? 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 and Starr 1982) and evolution (Fletcher et al. 2013), system and product design (Baldwin 2019; Guo and Gershenson 2004; Levin 2015), as well as management (Campagnolo and Camuffo 2009).

Simon (1991) stated that nearly decomposable systems, in which "the interactions among the subsystems are weak, but not negligible", are prominent. The concept of modularity can be used to judge how decomposable a system is. Modular systems have the ability to be disaggregated and recombined into new configurations with little loss of functionality due to the loose coupling effects between components. The opposite concept of modularity is synergistic specificity: systems that accomplish greater functionality by components being specific to one another and interact extensively with each other (Schilling 2000).

We assert that both modularity and synergistic specificity exist in the context of occupations. These concepts may not only provide structural information about occupations, but also help predict the trajectory of the future of work. Taking the terminology and concept from modular systems theory and combining it with network community detection techniques, we form a new approach that models the work ecosystem as complex systems of task components interacting with each other.

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 are seen as the next highest level below occupations and can be seen as the subsystems of occupations. In this work, we further associate tasks with skills and abilities to construct a network of tasks for each occupation. Skills and abilities characterize workers, and tasks represent occupations; together they constitute a network that allows us to look at the structure of an occupation and the dynamics between key elements in the work ecosystem. We seek to discover if there is a level between tasks and occupations: clusters of tasks we call task components.

This study is directed toward answering the following research questions:

(1) Are occupations modular? That is, do occupations share the same properties with many other complex hierarchic systems in terms of being decomposable into components?
(2) What role does technology advancement play in the decomposing and recombining the components of occupations?
(3) What are the driving forces in the evolution of occupations?

Exploring Occupation Networks

While government-supplied tabular data about labor has been extensively studied using econometric techniques, it has rarely if ever been treated as graph data. Treating it as graph data allows an analysis that takes advantage of network structure by detecting components. We note that new advances in databases and in machine learning have led to an increased interest in the creation of knowledge graphs, which can be used to support new forms of machine analysis performed through graph traversal in the form of random walks (Grover and Leskovec 2016; Perozzi et al. 2014; Xu et al. 2018). Consistent with this recent work, we conjecture that a graph-based approach may allow for the detection of previously unseen patterns in labor statistics.

We construct the networks from several datasets released by the Department of Labor in the form of the O*NET database, as these datasets reflect practice in the US economy. The datasets are collected through surveying job incumbents, occupational experts and analysts using standardized questionnaires. They are continually updated through conversations with a broad range of workers in all occupations. The O*NET database collects data on a wide variety of variables and scales, such as occupational characteristics and worker requirements. In its most recent release in February 2021, O*NET revised its occupation taxonomy to incorporate occupation changes. This release includes a total of 923 occupations in 23 major occupation groups. The approach described here has allowed us to analyze all occupations; for the purposes of discussion, we have provided examples from several of these occupations.

While O*NET data has been extensively studied using econometric techniques to understand and predict the US labor market (Frey and Osborne 2017; Manyika et al. 2017), it has, to the best of our knowledge, rarely if ever been treated as network data for building theories about task structures and occupation trajectories.

In order to construct occupation networks consisting of tasks, we further associate tasks with skills and abilities. This association was facilitated by a recent change to O*NET data: O*NET added work activities and skill/ability mapping in their 2020 release. In O*NET, there are seven skill categories and four ability categories. Each category includes more specific skills and abilities. A detailed list of the skills and abilities can be found in Table 1 below.

Since work activities are already mapped to tasks, as a result, each task is mapped to a combination of different skills and abilities. We then use this information to calculate the similarity between two tasks by dividing the number of shared skills/abilities by the total number of skills/abilities in both tasks. The similarity is used as the weight between the pair of tasks. If two tasks have no skill/ability in common, the similarity between them would be zero. Therefore, these two tasks are not linked. Similarly, if two tasks are associated with the same skill/ability combination, the weight of the link between them would be one, indicating the strongest link between them.

With tasks being nodes, and similarity between each node pair as the weight of the link, we can build a network for each occupation. Next, we run the community detection algorithm of choice on these networks to acquire partitions of tasks, the task components. We also compute the modularity of the partition of each occupation network.

As mentioned before, O*NET revised the occupation taxonomy in 2021. In order to compare occupation structural changes during the revision, we repeat the same computing process on two different data releases, one from before the revision and one from after.

Skills	Content	Reading Comprehension; Active Listening; Writing; Speaking; Mathematics; Science
	Process	Critical Thinking; Active Learning; Learning Strategies; Monitoring
	Social Skills	Social Perceptiveness; Coordination; Persuasion; Negotiation; Instrucing; Service Orientation
	Complex Problem Solving Skills	Complex Problem Solving
	Technical Skills	Operations Analysis; Technology Design; Equipment Selection; Installation; Programming; Operation Monitoring; Operation and Control; Equipment Maintenance; Troubleshooting; Repairing; Quality Control Analysis
	Systems Skills	Judgement and Decision Making; Systems Analysis; Systems Evaluation
	Resource Management Skills	Management of Financial Resources; Management of Material Resources; Management of Personnel Resources
Abilities	Cognitive Abilities	Verbal Abilities; Idea Generation and Reasoning Abilities; Quantitative Abilities; Memory; Perceptual Abilities; Spatial Abilities; Attentiveness
	Psychomotor Abilities	Fine Manipulative Abilities; Control Movement Abilities; Reaction Time and Speed Abilities
	Physical Abilities	Physical Strength Abilities; Endurance; Flexibility, Balance, and Coordination
	Sensory Abilities	Visual Abilities, Auditory and Speech Abilities

Table 1. O*NET Skill and Ability Structure[1]

Analysis of Occupations

Overall, we constructed task networks for 974 occupations with 18,713 tasks before taxonomy revision and 923 occupations containing 18,396 tasks after the revision. Among all occupations, the numbers of task components range from 1 to 5, and the modularity of occupations range from 0 to 0.556. Table 2 below

[1] There is a more detailed ability level that is not included in the table due to limited space. For a full list of skills and abilities with descriptions, please visit https://www.onetcenter.org/content.html

shows the distribution of task component counts of all occupations before and after the 2021 occupation taxonomy revision.

We can see that it is very rare for occupations to have only 1 component. This result answers our first research question: most occupations do exhibit some level of decomposability. There are also very few occupations including 5 task components, the maximum number of components in our data. This may indicate the practical problem of skill coverage in occupations: more than 5 task components in one occupation won't be practical given the skill/ability requirement and bandwidth of workers. The occupation may split into two or more occupations if it becomes too complex to keep the task components within a reasonable scale. However, this limitation may change when one or more task components can be partially or fully automated by technology. We will make conjectures about skill demands and allocation in the section that follows.

There is also a shift towards more task components after the taxonomy revision on the higher component count end. 10 more occupations have 4 task components and 2 more occupations have 5 task components when the total number of occupations reduces by 51 in the new taxonomy. This may be due to new occupations with more task components being added to the taxonomy, occupations split up without reducing their number of task components, as well as occupations with fewer task components disappearing or being merged into occupations with more task components. We will explain these scenarios further in the Conjecture section.

Number of Components	Before Taxonomy Revision	After Taxonomy Revision
1	4	3
2	353	319
3	485	457
4	125	135
5	7	9

Table 2. Occupation Counts by Number of Components

It is worth noting that having more task components doesn't always indicate higher occupation modularity. Occupation modularity depends on how tightly the task components are linked. Figure 2 shows examples of two occupation networks on both ends of the modularity scale. We provide these more detailed analyses of two occupations because they help illustrate the usefulness of the overall method.

While both occupations divide tasks into three components, the components are more intertwined for the occupation Data Scientists than the occupation Remote Sensing Technicians. When looking at the modularity of the two networks, Data Scientists on the left scores 0.07, and Remote Sensing Technicians on the right is 0.46.

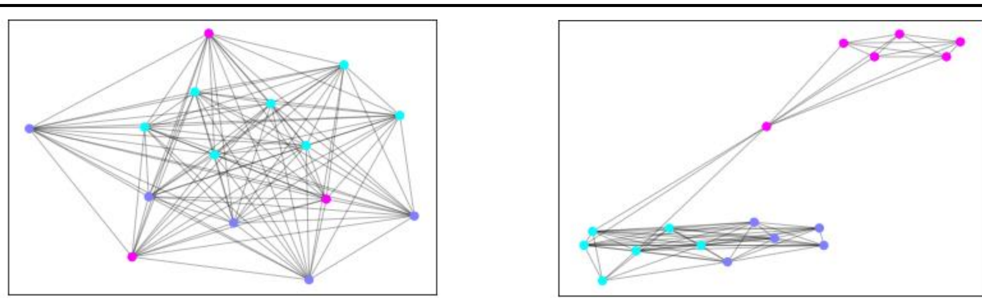

Figure 1. Occupation Networks of Data Scientists (Left) and Remote Sensing Technicians (Right)

In order to better understand the results, we take a further look at the tasks of both occupations and the components they belong to, as well as the skills/abilities they require (Table 3 and Table 4).

By comparing the two tables, we can see that the task components of the Data Scientists occupation share a lot of common skills and abilities, except for that component 1 includes a social aspect. However, for the Remote Sensing Technicians occupation, while component 0 and 1 both require basic skills (content and process), they can be distinguished because component 1 emphasizes technical skills and component 0 doesn't. Similarly, although components 1 and 2 both include technical skills, it is clear that component 2 has a physical element that component 1 doesn't.

Component	Task Statements	Skills/Abilities
0	Analyze, manipulate, or process large sets of data using statistical software.	Content, Process, Complex Problem Solving Skills, Technical Skills, System Skills; Cognitive Abilities, Sensory Abilities
	Apply feature selection algorithms to models predicting outcomes of interest, such as sales, attrition, and healthcare use.	
	Clean and manipulate raw data using statistical software.	
	Identify relationships and trends or any factors that could affect the results of research.	
	Identify solutions to business problems, such as budgeting, staffing, and marketing decisions, using the results of data analysis.	
	Propose solutions in engineering, the sciences, and other fields using mathematical theories and techniques.	
	Write new functions or applications in programming languages to conduct analyses.	
1	Apply sampling techniques to determine groups to be surveyed or use complete enumeration methods.	Content, Process, Social Skills, Complex Problem Solving Skills, System Skills, Resource Management Skills; Cognitive Abilities, Sensory Abilities
	Design surveys, opinion polls, or other instruments to collect data.	
	Identify business problems or management objectives that can be addressed through data analysis.	
	Read scientific articles, conference papers, or other sources of research to identify emerging analytic trends and technologies.	
	Recommend data-driven solutions to key stakeholders.	
2	Create graphs, charts, or other visualizations to convey the results of data analysis using specialized software.	Content, Process, Technical Skills; Cognitive Abilities, Psychomotor Abilities, Sensory Abilities
	Deliver oral or written presentations of the results of mathematical modeling and data analysis to management or other end users.	
	Test, validate, and reformulate models to ensure accurate prediction of outcomes of interest.	

Table 3. Task Component Partition Example — Data Scientists

Component	Task	Skills/Abilities
0	Manipulate raw data to enhance interpretation, either on the ground or during remote sensing flights.	Content; Process Cognitive Abilities, Psychomotor Abilities, Sensory Abilities
	Prepare documentation or presentations, including charts, photos, or graphs.	
	Correct raw data for errors due to factors such as skew or atmospheric variation.	
	Maintain records of survey data.	
	Document methods used and write technical reports containing information collected.	
	Provide remote sensing data for use in addressing environmental issues, such as surface water modeling or dust cloud detection.	
1	Consult with remote sensing scientists, surveyors, cartographers, or engineers to determine project needs.	Content, Process, Technical Skills; Cognitive Abilities, Sensory Abilities
	Adjust remotely sensed images for optimum presentation by using software to select image displays, define image set categories, or choose processing routines.	
	Merge scanned images or build photo mosaics of large areas, using image processing software.	
	Develop or maintain geospatial information databases.	
	Develop specialized computer software routines to customize and integrate image analysis.	
2	Collect geospatial data, using technologies such as aerial photography, light and radio wave detection systems, digital satellites, or thermal energy systems.	Technical Skills; Psychomotor Abilities, Physical Abilities, Sensory Abilities
	Calibrate data collection equipment.	
	Monitor raw data quality during collection, and make equipment corrections as necessary.	
	Operate airborne remote sensing equipment, such as survey cameras, sensors, or scanners.	
	Collect verification data on the ground, using equipment such as global positioning receivers, digital cameras, or notebook computers.	

	Collect remote sensing data for forest or carbon tracking activities involved in assessing the impact of environmental change.	

Table 4. Task Component Partition Example — Remote Sensing Technicians

The task statements also support this distinction: tasks in component 1 deal with using and developing information technologies, tasks in component 2 deal with physical equipment, and tasks in component 0 handle data records and documentation, which doesn't require the same level of technical skills compared to developing databases and software routines in task component 1. Conjectures about the relationship between modularity and combination of skills/ability will be made in the next section.

Both of these occupations deal with data and information technologies. However, the structures of these occupations are very different. While they are extreme cases and most occupations fall somewhere in between, they provide an illustration of how the community detection algorithm works and the difference between an integrated occupation (Data Scientists) and a modular occupation (Remote Sensing Technicians).

Conjectures

Our study focused on the structural properties of occupations by detecting task components based on the skills and abilities associated with each task. This method allowed us to compare occupations across the ecosystem. We found that occupations have different modularity levels given how much the task components are dependent on each other. We also examined occupation taxonomy changes over time and identified the driving forces behind these changes by looking into the task components. In order to better explain our findings and the potential of the method, we discuss specific examples that are pertinent to our research questions. We build a set of conjectures, and we describe how these conjectures might be tested.

Occupation Structural Comparison

When comparing structures of two occupations that belong to the same occupation group, a hierarchical classification determined by the Department of Labor, we expected to see similar partitions of task components. We often, however, discovered structural differences signaling key distinctions between occupations that are grouped together.

For example, under the occupation group "Librarians, Curators, and Archivists", we looked at the results of two occupations: Museum Technicians and Conservators, and Library Technicians. We noticed that Library Technicians are more complex. The occupation has 4 task components as opposed to 2 task components in the Museum Technicians occupation. The Museum Technicians occupation is more integrated — the 4 task components share more common skills and abilities, resulting in lower modularity (0.18). By contrast the 2 task components of Museum Technicians are much more separable, making it a more modular occupation: the modularity score is 0.44.

The reason behind this difference can be found in data describing the task components and their skills/abilities composition. One of the task components in the Museum Technicians occupation is only associated with physical abilities, therefore it is set apart from all the other tasks that require cognitive abilities and technical skills. As for the Library Technicians, even tasks with a physical aspect are often associated with other abilities and skills that relate to technology, systems, and management.

This observation prompted us to consider how physical and informational tasks stratify within an occupation, which leads to the following conjecture:

> *Occupations consisting of more simple task components emphasizing only one aspect of the skills/abilities are more likely to be modular and decomposable. By contrast, occupations with complex task components that combine multiple skill/ability categories equally tend to be more integrated.*

This conjecture might be tested in the following steps. First, aspects of skills and abilities might be classified into six categories: physical, cognitive, sensory, basic, technical, social. This is a simplified categorization based on the Skills and Abilities datasets in O*NET. Then the complexity of a task component can be measured by the number of skill and ability categories it includes. Last, regression analysis could be used to better understand the effects of occupation complexity and aspects of skills and abilities on occupation modularity.

It appears some occupations benefit from being more integrated and specific in their skills and abilities, while others are naturally modular. This may be related to the underlying skill and ability requirements of the occupations, the specificity of the technology involved, as well as other elements in the work ecosystem. Based on the study, we make the following conjecture:

> *Complex occupations that deal with specific technology and domain knowledge tend to be more modular, while occupations with lower complexity and tasks that utilize general technologies without needing deep domain knowledge tend to exhibit a more integrated structure.*

This conjecture might be tested by first calculating occupation complexity using the weighted occupation network created through our technique. Specifically, the complexity can be measured using the algorithmic entropy of the network (Morzy et al. 2017). Then regression analysis could be used to understand the relationships between occupation complexity and modularity.

Occupation Evolution

Our study also allowed us to compare occupations over time. We examined occupations that were changed during the 2021 taxonomy revision. There are three categories of occupation changes: 1) Rolled-Up Occupations: two or more occupations in the previous taxonomy were collapsed into one occupation in the revised taxonomy; 2) Split-Out Occupations: one occupation from the previous taxonomy was split into two or more occupations in the revised taxonomy; 3) New Occupations: an occupation in the revised taxonomy that had no starting profile information from the previous taxonomy (Green and Allen 2020).

Each category of occupation change occurred for several reasons, therefore not all changes from the same category follow the same pattern. We discuss these changes from the perspective of task components.

Rolled-Up Occupations

Occupations roll up when closely related occupations have one or more similar task components. When they merge, the similar task components are combined while the rest of the tasks are reorganized. For example, the occupation Financial Analysts and Investment Underwriters were rolled up to the occupation Financial and Investment Analysts. The two old occupations both have one task component that share 70% common skills and abilities, which include tasks that are cognitive and social. These two components are merged into one in the new occupation. The rest of the tasks from both old occupations are reorganized into two components: one focuses on the technical skill side, the other has an emphasis on system and management skills.

When occupations merge, it is also common to see new tasks being added and old ones being removed. This may affect the component partition for the new rolled-up occupation. This change of tasks happens sometimes because part of the original occupations becomes too specialized thus requiring a separate set of technical skills, and therefore it no longer fits in the current task component it belongs to. This phenomenon is sometimes coupled with part of the original occupations becoming less time consuming due to automation or other technological advancements.

For example, the occupation Broadcast News Analysts and the occupation Reporters and Correspondents merged into one after the taxonomy update: News Analysts, Reporters and Journalists. In its original form, Broadcast News Analysts is not a very complex occupation— only 2 task components and 8 tasks in total. In the past, these tasks may have taken an analyst long enough to complete that these tasks were enough for an occupation. However, modern technologies — particularly the ones that process and classify huge amounts of data and extract meaning from it — could increase an analyst's productivity, especially on tasks like "Analyze and interpret news and information received from various sources to broadcast the information" and "Examine news items of local, national, and international significance to determine topics to address, or obtain assignments from editorial staff members."

In our analysis, these tasks belong to the same component detected from the Broadcast News Analysts occupation. Some skills and abilities associated with this component include processes that machines are good at, including inductive reasoning, category flexibility, visualization, and selective attention, as well as processes that humans are good at including originality and critical thinking, making this task component a logical candidate for human/machine teams.

In addition to possible increased productivity for part of the original occupations, some tasks also got removed. For both original occupations, tasks related to editing — "Edit news material to ensure that it fits within available time or space" and "Edit or assist in editing videos for broadcast" — were removed. This is because editing has become more specialized with new tools and software available, therefore the editing aspect of the occupation has transitioned into more technical occupations. In fact, we find similar tasks in the occupation Broadcast Technicians and the occupation Audio and Video Equipment Technicians that handle editing broadcast materials.

These observations lead to the following conjecture:

> *Increased productivity or specialization due to technological advancements within one or more task components are precursors to occupational mergers. Task components that consist of a combination of skills and abilities that are suitable for full or partial automation are more likely to merge.*

This conjecture might be tested through experiment. A microcosm of small occupations would be defined with a set of tasks. Workers in a professional field might be randomly assigned technological tools with different abilities embedded in them, intended to help them complete certain tasks. These tools might be compared against current practice, and against alternative versions of the tools. The dependent variables of interest would be worker productivity, organizational configuration: how the workers hand off or delegate to the tools, and vice versa, as well as occupation evolution: small occupations may merge when certain tools are introduced.

Split-Out Occupations

When a relatively complex occupation adds on more tasks, or when the skills associated with its existing tasks become more advanced or specialized, the accumulated tasks and skills may become too much for one occupation to take on. Because of this, there may be a need to split up the occupation into more detailed and focused occupations. When this happens, we often see a portion of the tasks go into the split-out occupations unchanged as the new occupations are still closely related and would share common tasks, while the rest of the tasks go into different new occupations based on the specialty of each occupation. It is also common that one or more split-out occupations would maintain a similar structure as the original occupation.

The split doesn't always happen at the edges of task components. Some tasks in the same components will go into more than one of the split-out occupations. However, the tasks that aren't shared by the new occupations tend to be divided by their components.

For example, the occupation Web Developers in its original form already has 37 tasks across 3 components. Most of these tasks require a series of cognitive and technical skills. During the taxonomy revision, more tasks were added to this occupation, prompting a need to split it into two separate occupations: Web developers and Web and Digital Interface Designers. About half of the tasks from the original occupation went into both of the split-out occupations. The rest of the tasks from the original occupations were assigned to either one of the two new occupations.

One of the task components in the original Web Developers occupation has a focus on Technology Design skill. There are 10 tasks in total in this component. Five of them were kept by both split-out occupations. Four out of the five tasks left in this component went into the Digital Interface Designers occupation. Some examples include "Incorporate technical considerations into Web site design plans, such as budgets, equipment, performance requirements, or legal issues including accessibility and privacy" and "Develop Web site maps, application models, image templates, or page templates that meet project goals, user needs, or industry standards". For the other two task components in the original occupation, aside from the tasks that were kept by both spit-out occupations, most of the rest of the tasks went to the new Web Developers occupation.

In this case, most tasks still stay in the component they were previously part of, making the two split-out occupations structurally similar to the previous occupation while having different specialty task components. This is not always the case. Sometimes when an occupation splits, closely related task components in the original occupation contribute to one of the split-out occupations. The resulting occupation will have a list of tasks that are closely related to each other, making it a highly integrated occupation with low modularity even when the original occupation is more modular.

For example, the occupation Histotechnologists and Histologic Technicians were split into two occupations: Histotechnologists and Histologic Technicians. There are three task components in the original occupation, two of which are physical. They differ as one of them handles specimens and tissues directly, the other deals with lab equipment. During the split, both of these components contributed tasks to the occupation of Histology Technicians. While there is still a distinction between these two components in the new occupation, without the third component in the original occupation that emphasizes social skills, the new Histology Technicians occupation becomes much more integrated. Meanwhile, more tasks that require cognitive skills — in particular social skills — are added to the other new occupation Histotechnologists, making it more modular than the original occupation.

This observation shows that occupation splits often happen on a task component level albeit not always along task component boundaries. The structures of the resulting occupations depend on how the task components are divided during the split.

Similar to the fact that a system's context may create forces that draw the system toward a particular state, either modular or integrated (Schilling 2000), socio-technical changes in the work ecosystem can also create pressure that drives the decomposing and recombining of tasks and skills. For example, an occupation can reach a skill ceiling when there are too many different skills required by its tasks, or when part of its tasks involve technologies that are becoming more advanced therefore require more specialized skills and training. This could create a pressure for the occupation to split up. By splitting up, part of the occupation can still maintain its modularity while the other part becomes more concentrated on the specialty and skill sets that prompted the split. The balance between specificity and modularity within an occupation can change with the change of its context. Therefore, we make the following three part conjecture:

> *When an occupation becomes too complicated or some of its tasks become more specialized due to socio-technical changes including technological advancements, increasing demand of certain skills, the occupation reaches a skill ceiling, creating a need for its tasks and essential skills to be redistributed.*
>
> *The redistribution of skills may happen through splitting an occupation into more occupations, because as occupations become more complex, institutions struggle to find single individuals who have all the skills necessary, and begin searching for those who are good at a subset of skills in an occupation. Over time, this leads to different career paths, and, eventually, new occupations.*
>
> *When the goal of splitting is to separate one aspect of the skill/ability combinations from the original occupation, the resulting occupation tends to become a highly integrated one. When the goal of splitting is to enable different specializations, the resulting occupations will tend to maintain the original structure.*

This conjecture might be tested by a series of steps. First, data related to work and skills could be analyzed to understand skill demand and training requirements, especially for technical skills. This analysis might include observing how demand increases, testing to see if demand approaches a limit — that is, if the best fit model for skill demand change is a line or an S-curve. We note that predicting labor force trends using econometric data is not easy, and economists have a checkered history of making such predictions, in part because data is noisy, and smoothing in response creates another problem by disguising inherent signals. To better discover the underlying mechanisms of work ecosystems, future research might use experiments in microtask environments such as those in crowd labor marketplaces.

While occupations are complex conceptualizations that change slowly, a parallel and faster speed evolution of skills and skill clusters that form what we might call proto-occupations occur in crowd work (Kittur et al. 2013). This smaller faster environment might be used to understand the possible mechanisms that drive the evolution of occupations. Two types of participants might be used in experiments: those who write task descriptions and recruit and train crowd workers, and those who perform work. By creating a cost associated with not being able to recruit and train appropriate workers, those who write the task descriptions may be put in a situation analogous to company recruiters that need to build career ladders for workers.

For example, in one such experiment, participants would be asked to write descriptions of crowd-based human intelligence tasks consistent with a proto-occupation that involves task components with different technical skill requirements, modeled on the results of the observational study. Then more tasks that involve different or more advanced technical skills, or different specialties could be added to the participants' workload, thus increasing the complexity of the proto-occupations gradually. By observing how the participants breakdown work and organize tasks in different scenarios, we might discover how they react to the predicted skill ceiling and what skills or technology demands would most likely prompt a split in the proto-occupation, as measured by the changes in descriptions and training strategies.

These experiments could lead to a model of skill ceiling effects, that might be used to evaluate policies that consider retraining as a result of job dislocations due to advances in technology.

New Occupations

A new occupation in the revised taxonomy is defined as an occupation with no starting profile information from the previous taxonomy (Green and Allen 2020). However, by comparing task components of the new occupations to existing occupations, we find that most new occupations can be seen as a recombination of different task components from existing occupations in terms of skills and abilities. We also notice that the occupations with closely related task components don't always belong to the same occupation groups.

New occupations don't emerge out of thin air. Their roots are embedded in the networks of existing occupations. However, some new occupations are more loosely connected to the existing work ecosystem than the others. This can be observed when these new occupations have relatively original task components. For example, among the five task components of Blockchain Engineers, the most similar task components we find in existing occupations only share 75% of the task and abilities. With these observations, we make the following conjecture:

> *When a new occupation is added to the occupation taxonomy due to new technology or processes becoming more prevalent, it is unlikely there will be similar task components in existing occupation networks. These rarer combinations of skills and abilities may be signaling growth in employment and outlook of occupations.*

This conjecture can be tested by regression models using data from the US Bureau of Labor Statistics on employment projection. Skill and ability combinations can be used as independent variables to predict occupation growth.

Conclusion

The evolution of work is a complex, layered process. It is influenced by a wide range of socio-technical factors and would in turn have many societal impacts. This paper has sought to build theories and methods that can be used to study the future of work from a systematic perspective. We now summarize what we found in relation to our research questions.

In answer to research question one, we found that occupations are indeed modular. This finding is a result of an analysis of the structural properties of occupations. While some occupations are more modular than others, they all, to a certain degree, share the same properties with other complex hierarchic systems when being decomposed into components. We also noticed that occupations with simple task components emphasizing only one aspect of the skills/abilities are more likely to be modular, and that occupations dealing with specific technology and domain knowledge tend to be more modular. This last observation helps answer the second research question on the role of technology: technology with a low level of complexity and a high level of specificity is often associated with more modularity in occupations.

By examining the structural changes of occupations over time, we made the following observations in relation to question three, which seeks to better understand the evolution of occupations. Increased productivity or specialization due to technological advancements can lead to occupational mergers. Task components that consist of a combination of skills and abilities that are suitable for full or partial automation are more likely to merge. On the other hand, increased complexity or demand for specialized skills due to socio-technical changes can create the need to redistribute tasks through occupation splits. Moreover, new technology or processes being adopted in the workplace can result in new occupations being created. These observations can help us further understand the driving forces in the evolution of occupations, especially the role technology plays in the structural changes of occupations.

This paper uses network-based techniques because they have been successful in predicting relationships and innovations. We showed that the network-based methods can capture more deeply embedded relational and structural information about work, suggesting they will prove more effective than other methods commonly used for predicting the future of work. Changes in work are not only associated with technological changes but with an interrelation among skills, abilities, and technologies.

In summary, by theorizing occupations and tasks as complex systems and subsystems that interact and coevolve with other elements including technology, skills, and abilities, our study combines network theory and modular systems theory by describing a new method of analyzing dynamic work ecosystems. Based on observations from an analysis of occupation structures and evolution using the described research methods, we suggest possible ways of better understanding the future of work.

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