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Assessing Job Interrelatedness: Data Sources to Facilitate Job Transition and the Future of Work

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Given the significant impact technological advances such as artificial intelligence (AI), machine learning (ML), big data, cloud computing, and advanced robotics are having on the business environment, many believe we are entering a fourth Industrial Revolution (Ghislieri et al., 2018; Schwab, 2016). This transformation is unique given the speed at which new ideas and technology are impacting businesses and employees (Rainie & Anderson, 2017; Shadovitz, 2019). Specifically, the Organisation for Economic Co-operation and Development (OECD, 2019) estimates that 14% of jobs across its member countries could disappear because of automation in the next 15 to 20 years, and another 32% are likely to change significantly. As a result, there is a need to be able to accurately examine the interrelatedness of jobs so that organizations and individuals will be adequately prepared to transition away from jobs that are decreasing (or changing significantly) to jobs that are in higher demand, holding steady in the economy, or emerging due to changes such as increased technology.

More recently, the COVID-19 pandemic has solidified the need to examine job interrelatedness, as additional jobs have been impacted due to businesses closing or increased demand in some segments of the economy (Lund et al., 2021). For example, during the height of the pandemic, in the healthcare field, there have been shortages in some positions (e.g., respiratory therapists), but a surplus in others (e.g., nurse anesthetists, due to a decrease in elective surgeries), leading to the possibility of backfilling high-need jobs quickly with those that are in surplus during a global pandemic. In the longer term, certain jobs in industries such as hospitality and transportation may decline, causing employees in these industries to need to look for alternative employment options.

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This brief describes several data sources that can be used to examine the interrelatedness of different occupations. These sources include information on job responsibilities (e.g., work activities and tasks), employee characteristics (e.g., knowledge, skills, abilities, and competencies), and trainings or other measures of capabilities acquired; all of the sources described are publicly available. Analytic techniques such as the use of machine learning (ML) and artificial intelligence (AI) to rapidly analyze and aggregate this type of data more effectively and efficiently are also discussed. The desired outcomes from analyses of these data would be for individual employees to be able to identify jobs that are related to their prior job or their current skill set; for employers to determine what jobs or skill sets are related to their current and future job needs; and for the workforce system to make determinations about where to invest in training programs or what jobs to guide people towards when they are looking for new work. A case study conducted by the American Institutes for Research (AIR) provides a specific example of how these data sources were used to examine the respiratory therapist occupation.

O*NET Data

The Occupational Information Network (O*NET) online database is a source of occupational information developed under sponsorship of the United States Department of Labor (DoL) Employment Training Administration. It contains hundreds of standardized and occupation-specific descriptors for almost 1,000 occupations covering the entire U.S. economy, and the information is all publicly accessible (www.onetonline.org). Given the breadth of information contained within the O*NET online database it serves as a logical starting point when examining job interrelatedness.

For each occupation listed within O*NET there is the option to look at "related occupations," which lists the 10 occupations that O*NET has identified as being most closely related to the occupation (e.g., having the greatest overlap in knowledge, skills, and abilities). For example, for respiratory therapists, occupations such as radiation therapists, cardiovascular technologists and technicians, and diagnostic medical sonographers are listed as related occupations within O*NET (Respiratory Therapist O*NET Summary Report). Additionally, each occupation contains a set of Detailed Work Activities (DWAs), which are a subset of an overall list of common work activities required across occupations. Therefore, those occupations with the greatest amount of overlap on DWAs are likely closely related. Similar to the DWAs, there is a standardized list of Tasks across all occupations, and occupations with overlapping Tasks are also likely to be closely related.

Additional O*NET data categories such as Knowledge, Skills, and Technology Skills can be examined to further determine job interrelatedness. Notably, focusing on Knowledge, Skills, and Technology Skills allows for comparisons of occupations focusing specifically on the most in-demand aspects of the identified occupations.

While the information contained within O*NET can be helpful in examining the interrelatedness of occupations, there are challenges and limitations that need to be considered. Specifically, the level of detail associated with each element can make it challenging to verify interrelatedness. For example, while skills such as Service Orientation, Complex Problem Solving, Time Management, and Science are defined to allow them to apply across a broad range of occupations, the lack of specificity in these skill definitions makes it challenging to confirm that they are operationalized in the same way across occupations, and to determine whether the same proficiency level is needed across occupations. The same is true for the DWA, Task, and Technology Skills data. So, the O*NET elements may make some occupations look similar on the surface even if the specific operational definitions for each occupation may be very different.

In addition to the concern of specificity in the O*NET data elements, conducting a comparison across occupations can also be quite labor intensive. While related occupations can be immediately identified in O*NET, comparing data elements across occupations is typically a manual process that requires interpretation of the targeted elements. Specifically, some level of subject matter expertise is needed to verify the interpretation of the data elements, along with the interrelatedness across occupations. Final confirmation of interrelatedness from subject matter experts (SMEs) will still be needed unless greater specificity can be added to the element definitions or found in other data sources.

Practice Analysis Data

A practice analysis describes the job responsibilities of the incumbents within an occupation. A typical practice analysis contains a detailed list of the primary or critical tasks that are performed on the job, along with the knowledge and skills needed to successfully perform these tasks. The content of the practice analysis often serves as the test blueprint when developing an assessment to verify that an individual possesses the knowledge and skills needed to successfully perform the job (e.g., for licensing purposes), or to determine what training/developmental areas are needed to achieve minimum proficiency in an occupation (e.g., in the context of professional development planning).

One strength of a practice analysis is that the information included is typically very detailed, therefore allowing for very fine-grained comparisons when looking at occupational interrelatedness. So while the data elements within O*NET provide a structure that is standardized across occupations at a high level, the practice analysis data provide more detailed information to allow comparisons across occupations to focus on data elements at a more granular level (and often at a defined proficiency level). This level of detail will better ensure that selection/assessment, training, and licensing content are focused on the desired level of competence and proficiency needed to successfully perform within the targeted occupation. Additionally, the information included in a practice analysis has typically been validated through SME input. As a result, comparisons across occupations can be made by trained job analysts to determine the overlap between occupations.

While there are benefits of using practice analysis data (relative to O*NET data) to examine job interrelatedness, there are still challenges and limitations that exist. For example, practice analysis data do not always exist for an occupation, and there can also be variations between practice analysis procedures, rating scales, and amount of documentation, which can sometimes make comparing occupations challenging. Additionally, similar to the use of O*NET data, comparing occupations based on practice analyses is typically quite labor intensive, and some level of SME input is still needed to verify technical aspects of the comparisons and to confirm similarities or differences that may not be as obvious to the job analysts.

Curriculum Data

Information on the curricula associated with particular occupations can also be used to examine job interrelatedness. Specifically, courses and course requirements can be compared to determine similarities and differences across occupations. A strength of using course data is that the content covered via each course should be an accurate estimate of the knowledge (and possibly skill) possessed within an occupation. Further, if it is possible to compare curricula for related occupations *within the same institution* (e.g., a given college or university), then the resulting assessments of similarities and differences are likely accurate, given the strong interrelatedness of courses within academic programs at the same academic institution.

However, a challenge of using curriculum data is determining which institutions to include to ensure representativeness. For most occupations, there are likely dozens of programs across academic institutions that could be compared, so determining which ones to use in the comparison to ensure a

representative comparison is being made is important. For example, since it is likely that only a sample of programs will be included in the comparison, determining how to select the programs can be challenging (e.g., selecting programs with a large number of graduates, selecting programs that are recognized as leaders within an occupation). Additionally, for some occupations there may be a range of degrees associated with that occupation (e.g., associate's, bachelor's, master's, Ph.D.), so the comparison may need to focus on a range of degrees to gather an accurate summary of likely courses completed. But this may also make an equivalent comparison more challenging. And using curriculum blueprints offered or endorsed by professional associations or accrediting agencies may increase the likelihood that the content of curricula across institutions is comparable. But similar to the practice analysis data, curriculum blueprints may not be available for comparison across a wide range of institutions or span across the targeted range of occupations. Finally, similar to both the O*NET and practice analysis data, conducting a comparison of curriculum can be quite labor intensive, and then also still require SME input to verify that the content covered in each course is similar/different.

Machine Learning (ML)/Artificial Intelligence (AI) Data Output

ML and AI are technologies that allow one to classify and cluster data elements and identify patterns to predict relationships. So, these are not additional data sources to be used to compare occupations, but rather methodologies that could be used to expedite the comparison of data sources (e.g., O*NET, practice analysis, curriculum). The strength of using ML to examine job interrelatedness is that it could allow for comparisons to be conducted quickly across multiple occupations using data such as O*NET's Tasks, Knowledge, Skills, and Technology Skills data categories. Similarly, for practice analysis data, ML could be used to conduct comparisons across multiple occupations quickly. And for curriculum data, ML could be used to examine the data across numerous programs and institutions, resulting in output that is representative of the population of individuals associated with an occupation.

However, there are still challenges associated with ML and AI. For example, the algorithms used in ML to make these processes operate more quickly take time to develop. Specifically, it would take time to train an algorithm to be able to sift through the available data and accurately identify similarities across occupations. Additionally, algorithms used in ML can be impacted by biases that may lead to an inaccurate identification of similarities. Related to this is that the data sources and data elements that are included in the ML need to be accurate and well defined. It not, the training of the algorithms may be insufficient or inaccurate, thereby leading to an inaccurate determination of job interrelatedness. So, while there are entities that have been using ML to leverage existing data (e.g., O*NET, curricula, job announcements) to search for job interrelatedness, the level of specificity (and target proficiency level needed) can still remain a challenge. These ML processes may work well for technology-related occupations that focus on the systems, languages, or programs needed to be successful within the occupation. But a consistent level of specificity for the data elements, including how important the data elements are and the proficiency level needed to be successful, does not always exist across occupations (or the career levels within an occupation).

Additional Data Sources

In addition to the data sources mentioned here, there are data elements that may also be used to further examine job interrelatedness. For example, job announcements, performance plans, and career plans all contain information to describe jobs and what is needed to be successful within the job. This information could be examined using ML to further refine the criteria for determining job interrelatedness.

Also, the examination of interrelatedness described has primarily focused on the occupational level. This is useful when looking across the U.S. marketspace, or even internationally, as there is standardization in these environments when describing an occupation. However, there may be nuances when looking at jobs or positions across an industry or even across a subset of employers. The job elements associated with these may be more detailed, which would allow for more accurate determinations of job interrelatedness, albeit in a more limited environment of a specific industry or set of employers.

Summary

There is a substantial amount of data that can be leveraged to explore interrelated jobs and allow employees and employers alike to prepare for successful occupational transitions as the future of work continues to change. O*NET remains a solid starting point, given the standardized structure associated with the many data elements across occupations. Additional data should be used to provide greater specificity for the elements so they can be used to accurately identify interrelated jobs and gain the necessary skills (at the appropriate proficiency level) to be prepared to successfully transition to a new job or occupation. The specific type of additional data will likely be driven by what data exists for the target occupation, with the understanding that using multiple sources of data will likely result in more accurate (and specific) results. The use of ML to identify interrelated occupations (based upon tasks and duties performed, knowledge or skills possessed, trainings or experiences completed) will allow for multiple data sources to be more easily used. But, while ML output using multiple sources of data should result in more specific information than just relying on O*NET, the ML output should indicate how important the resulting data elements are for each occupation as well as the proficiency level needed to be successful at the targeted career level within the occupation. Otherwise, this could make an occupational transition both challenging and frustrating for an individual if they do not understand exactly what developmental areas they need to focus on to successfully switch occupations. It may also prevent job transitions from occurring rapidly if an event similar to COVID-19 were to occur again.

References

Ghislieri, C., Molino, M., & Cortese, C. G. (2018). Work and organizational psychology looks at the fourth industrial revolution: How to support workers and organizations? *Frontiers in Psychology, 9.* https://www.frontiersin.org/articles/10.3389/fpsyg.2018.02365/full

Lund, S., Madgavkar, A., Manyika, J., Smit, S., Ellingrud, K., Meaney, M., & Robinson, O. (2021). *The future of work after COVID-19.* McKinsey & Company Report. https://www.mckinsey.com/featured-insights/future-of-work/the-future-of-work-after-covid-19

Organisation for Economic Co-operation and Development. (2019). *OECD employment outlook 2019: The future of work.* OECD Publishing. https://doi.org/10.1787/9ee00155-en

Rainie, L., & Anderson, J. (2017). *The internet of things connectivity binge: What are the implications?* Pew Research Center. https://www.pewresearch.org/internet/2017/06/06/the-internet-of-things-connectivity-binge-what-are-the-implications/

Shadovitz, D. (2019, April 11). *Disruptive tech and the future of HR.* HR Executive. https://hrexecutive.com/disruptive-tech-and-the-future-of-hr/

Schwab, K. (2016). *The Fourth Industrial Revolution: What it means, how to respond.* Geneva: World Economic Forum. https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/

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