How science and technology developments impact employment and education

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Edited by Katy Börner, Indiana University Bloomington, Bloomington, IN, and accepted by Editorial Board Member Pablo G. Debenedetti October 8, 2018 (received for review March 6, 2018)

A better understanding of how developments in science and technology influence the creation of new occupations and subsequent changes in educational programs can help decision makers at all levels of our society. As a result of research and development efforts, innovations are achieved, resulting in the creation of new occupations and the demand for employees with expertise in these new areas. To fulfill the demand, universities and colleges often revise their programs to address these needs. Several data sources are described in this paper that might help us to explore the relationship between advancements in industry, emerging occupations, and educational changes over time.

job analysis | emerging occupations | R&D funding | population projections

In this paper, I explore how one might understand the way advances in science, engineering, mathematics, and technology impact employment and education, with the ultimate goal of possibly predicting when these changes are likely to occur. The overall concept is that new developments in science and technology become widely applied in industries as they are expanded and improved upon. This results in a demand by employers for expertise in the new areas and often results in new occupations being defined. It is usually at this point that universities and colleges revise their programs to address the need by employers to fill new occupational specialties. For example, the demand by employers for expertise in big data, predictive analytics, and machine learning in the past 5 y or so has prompted many universities to create degree programs in data science.

I describe several data sources in this paper, most of which come from the US Federal Government. We need information on all stages of the process over time (i.e., advances in science and technology, changes in employment and industry, and new degree and certificate programs at universities) to understand the historical trends and how the separate pieces interact. The most useful information will likely come from changes in occupation and industry, which should be reflected in classifications systems like the North American Industry Classification System (NAICS) and the Standard Occupational Classification (SOC) system. Thus, I describe these systems in this article.

The United States has provided federal funding for research and development (R&D) for many years, with the largest shares going to the Department of Defense, Department of Health and Human Services, Department of Energy, National Science Foundation (NSF), NASA, Department of Agriculture, and Department of Commerce (1). We can use information about government funding programs, published timelines for disciplines (e.g., computer science, statistics, mathematics, science), and data from the National Center for Science and Engineering Statistics to establish the historical trends in science and technology developments.

Throughout the article, I propose some research directions to explain these interactions based on historical trends and changes in science and technology developments, occupations, and university environments.

Employment Projections from the Bureau of Labor Statistics

The Bureau of Labor Statistics (BLS) has been publishing employment projections since 1960, with the goal of providing information on career opportunities to students, jobseekers, and policy makers. Every 2 y, the BLS publishes projected employment 10 y into the future for over 300 different industries and 800 occupations. The latest projections for the period 2016–2026 were published in October of 2017 (2). I describe the process here because it informs our concept of the interactions between industry and occupational employment.

The employment projection process involves a series of six major modeling steps, as illustrated in Fig. 1 (3). Each of these steps is based on different models, processes, and associated assumptions (4). It is important to note that important assumptions are made at the different modeling steps, such as the full employment assumption in the macromodel used for aggregate economy projections. All modeling assumptions are clearly described by the BLS (4).

The overall logic for the process follows. First, a major driving force for future employment is the number of people in the labor force. The number of available workers will, in turn, affect the possible level of productivity and demand in the future economy. This subsequently drives the industry output and employment needed to achieve the projected level of productivity and demand. I provide a brief overview of these steps; more information is provided on the BLS Employment Projections website (5).

Labor Force Projections. The BLS obtains labor force projections for the target year by using data from the Census Bureau's projections of the resident population of the United States (6). The Census Bureau projects the size of the population based on different assumptions (high, midlevel, and low) regarding fertility, mortality, and net international migration. The BLS uses the midlevel projection. Net international migration has a direct impact on all age groups and has the potential to significantly alter the composition of the future labor force, as well as the projected composition of the gross domestic product (GDP).

The future resident population level has to be converted to the projected civilian noninstitutional population. Children will not be in the labor force, so the projected number of children from 0–15 y of age is subtracted. Next, the number of people in the Armed Forces is subtracted to get the projected civilian

This paper results from the Arthur M. Sackler Colloquium of the National Academy of Sciences, "Modeling and Visualizing Science and Technology Developments," held December 4–5, 2017, at the Arnold and Mabel Beckman Center of the National Academies of Sciences and Engineering in Irvine, CA. The complete program and video recordings of most presentations are available on the NAS website at www.nasonline.org/modeling_and_visualizing.

Author contributions: W.M. wrote the paper.

The author declares no conflict of interest.

This article is a PNAS Direct Submission. K.B. is a guest editor invited by the Editorial Board.

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Published online December 10, 2018.

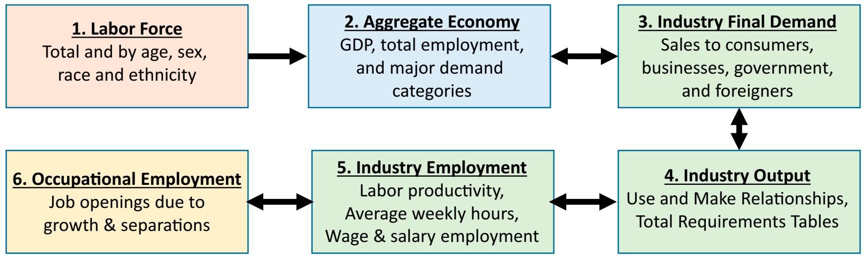

Fig. 1. These six steps provide an overview of the process the BLS uses to project employment 10 y into the future. We can think of these as four major aspects of the process: (*i*) the size of the future population determines the labor force, (*ii*) the labor force drives the possible size of the future economy, (*iii*) certain industry and employment levels will be needed to achieve the future economy, and (*iv*) industry demand determines future occupations and job openings (3). Reprinted from ref. 3.

population. This is done for categories based on age, gender, race, and ethnicity. An estimate of the number of people in institutions (e.g., prisons, nursing homes) is also subtracted from each group.

The conversion from the noninstitutional resident population to the labor force is needed to match the labor force participation rates obtained from the Current Population Survey. The labor force participation rates are projected to the target year by first smoothing the rates based on running medians, transforming the smoothed rates to logits, fitting a straight line, extending to the target year, and transforming back to rates. The projected participation rate for each group (age, gender, race, and ethnicity) is multiplied by the corresponding projection of the civilian noninstitutional population. This yields the projected labor force for each group, which are added together to produce the total civilian labor force.

Projection of the Aggregate Economy. The projected size of the future labor force is an important variable used to produce macroeconomic projections of the aggregate economy, which is the next step in the process. The BLS uses a model licensed from Macroeconomic Advisers, LLC. The model is designed to reach a full-employment solution at the end of the target period. [This assumes that any unemployment is frictional (employees leave to get a better position) and there is enough demand for everyone to work who wants to do so.] Besides the size of the labor force, other external variables in the model are energy prices and assumptions about fiscal policy. This model provides information on projected employment, output, prices, productivity, and more. The most important variables for projected employment are nonfarm payroll employment, labor productivity, and GDP. These variables constrain the industry output and employment projections.

Industry Projections. The projected demand is a key factor in determining future jobs. In this step, the projections of final demand from the macroeconomic model of the economy are disaggregated into detailed categories. These are used to estimate the types of commodities purchased within each of these categories. The output is a final demand matrix, where the rows correspond to demand categories and the columns represent commodity groups. This results in a detailed distribution of the GDP, which provides the demand component of an interindustry model of the economy.

The GDP looks at sales to final purchasers and not at the intermediate purchases required to create the final product. For example, the GDP would include the purchase of a car, but not the steel used to build it. The input-output (I-O) model in this step of the process yields an industry-level estimate of the output and employment required to produce a given level of GDP.

The I-O model requires four tables. The use table shows the use of commodities by industry, and the make table indicates the commodity output of each industry. These are converted to coefficient form and then used to derive the direct requirements table and the market share table, respectively. The direct requirements table shows how industry uses commodities in its production process, and the market share table indicates the commodity output of each industry.

A relationship derived by the Bureau of Economic Analysis converts a projection of commodity demand into a projection of industry output, using the direct requirements and market share tables, as shown here:

$$\mathbf{g} = \mathbf{D}(\mathbf{I} - \mathbf{BD})^{-1}\mathbf{e},$$

where $\mathbf{g}$ is a vector of domestic industry output by sector, $\mathbf{B}$ is the direct requirements table, $\mathbf{D}$ is the market shares table, and $\mathbf{e}$ is a vector of final demand by commodity sector.

The employment required to produce the projected industry output is determined next. Industry output, industry wage rate relative to output price, and time are used in a regression model to estimate hours worked by industry. Average weekly hours for each industry are also estimated as a function of time and the unemployment rate in this modeling step. These data on hours are used to derive wage and salary employment by industry.

Occupational Employment. The BLS produces occupational employment projections in this final step and publishes them in the National Employment Matrix. This matrix provides information on employment in detailed occupations within wage and salary industries and for different classes of workers. These are counts of nonfarm wage and salary jobs (the largest group), self-employed workers, agricultural industry workers, and workers in private households. This information is provided for the base year and the target year.

The BLS explores several factors that can affect the demand for an occupation within an industry. These include technological innovation, changes in production methods, replacement of a product, and more. It is interesting to note that the BLS also models and estimates the number of job openings resulting from separations due to employees migrating to other positions or leaving the labor force and includes this information in the National Employment Matrix.

Industry and Technology Developments

NAIC System. Changes in industry demand and technological innovations are important factors affecting future occupational employment, as we saw in the previous section. Furthermore, the projected employment published by the BLS is given for detailed industries and occupations. Thus, I describe the industry classification systems used by the BLS and other federal agencies. These systems provide a framework for assigning codes to establishments, allowing for consistent data collection and analyses of economic statistics in industries over time.

Federal statistical agencies used the Standard Industrial Classification (SIC) system in 1939 when it was first published by the former Bureau of the Budget, which is now the Office of Management and Budget (OMB). Like all classification systems, it was updated periodically. However, economic changes, such as the emerging services-oriented economy, increased use of computers, rapidly evolving technology, and globalization, motivated the need to change the industry classification system.

In 1992, the OMB created the Economic Classification Policy Committee to develop a new industry classification system. The committee worked with statistical agencies in Canada and Mexico to develop the NAICS. In contrast to the SIC system, this system was based on production, which eliminated definitional differences and focused on emerging economic activity. The NAICS was first introduced in 1997 partly to account for the increase of services relative to manufacturing, which needed to be accounted for in an industry coding system. The NAICS is reviewed periodically to reflect changes in the North American economies (7, 8).

The NAICS uses a six-digit hierarchical coding system. It categorizes economic activity into 20 industry sectors. These sectors can be grouped into those that are mainly goods-producing or services-providing sectors. As an example, a sampling of NAICS codes at the two-digit level is shown in Fig. 2. Economic analyses often use finer detailed NAICS codes at the three-digit or even the six-digit level.

Developments in Science and Technology. Funding provided by the US Federal Government is perhaps one of the main drivers spurring developments in science and technology by industry and academia. Understanding government investment in R&D will help inform how technology has been advanced over the years. An excellent resource for historical information and data on federal funding by agency for R&D is available from the American Association for the Advancement of Science (AAAS) (9).

Program officers and managers in federal funding agencies devise research programs based on their understanding and knowledge of emerging developments in science and technology. Their motivation is to fund promising new ideas and research for the benefit of our nation and to promote innovation. For example, federal dollars invested in the development of new drugs save lives and create new jobs.

- Goods-Producing
  - Natural resources and mining
    - Sector 11 (Agriculture, forestry, fishing, and hunting
    - Sector 21 (Mining)
  - Construction
    - Sector 23 (Construction)
  - Manufacturing
    - Sector 31 - 33 (Manufacturing)
- Service-Providing
  - Trade, transportation, and utilities
    - Sector 42 (Wholesale trade)
    - Sector 44 - 45 (Retail trade)
    - Sector 48 - 49 (Transportation and warehousing)
    - Sector 22 (Utilities)
  - Information
    - Sector 51 (Information)

Fig. 2. Sample of two-digit industry codes based on the NAICS hierarchy.

Department of Defense (DoD) agencies associated with the Army, Navy, and Air Force have a history of funding work on basic and applied research, and the DoD has the largest share of federal R&D dollars (9). The DoD funding agency that has been around the longest is the Office of Naval Research (ONR) (10). The ONR was established in 1946 to continue the collaboration between government, academia, and industry started during World War II, which resulted in many technological innovations. It is interesting to note that the ONR predates the NSF, which was founded in 1950.

I discuss how to gather historical information on federal funding for R&D using the ONR as an example. A research agenda and calls for proposals are published in solicitations or broad agency announcements. Current and past solicitations for their programs are available on the ONR website (11) and should be similarly available on other funding agencies' websites. There are two other potentially useful sources of data on funding: the Small Business Innovation Research (SBIR) program and the Multidisciplinary University Research Initiative (MURI). These two programs are associated with all arms of the military, not just the Navy.

The MURIs are large efforts funding interdisciplinary teams of academic researchers. The topics are proposed annually by DoD program officers and are selected based on their potential for producing dual-use technologies critical for national defense and commercial applications. The MURI awards are typically funded at a much higher level than single-investigator awards to foster innovations and to accelerate the research.

The SBIR program provides funding to small businesses to support and stimulate technological innovation in industry. Like the MURI program, SBIR topics are developed by program officers in participating federal agencies (12), and they reflect opportunities to further develop and commercialize advancements in research and technology. SBIR topics for the past 10 y are available on the web (13).

Business and industry also fund R&D. Data on these investments have been collected via the Business R&D and Innovation Survey, which is a survey conducted by the Census Bureau for the National Center for Science and Engineering Statistics (14). This is an annual survey of companies in manufacturing and nonmanufacturing industries. The survey provides information on funding levels, type of funding, employment, occupations, innovations, and intellectual property for various NAICS levels.

Timelines in Science and Technology. Timelines for major advancements in various disciplines, such as mathematics, statistics, computer science, physics, and engineering, can also be informative. These exist on the web, and a simple search will provide many resources and timelines. However, web-based sources can be unreliable and error-prone, so it is wise to use data from government agencies, reputable companies, and professional associations.

Other potential sources of information on how science and technology change over time are the professional associations, such as the AAAS, the Association for Computing Machinery, and the American Physical Society. These large professional societies often have groups that focus on specific topic areas in their discipline. The historical development of these groups can provide a timeline of advancements in science and technology. For example, the American Statistical Association (ASA) has sections focusing on specific areas or applications of statistics. These sections are usually established once there are sufficient advancements in the area and membership to justify the section. Fig. 3 shows when ASA sections were established and includes some interesting milestones along the way.

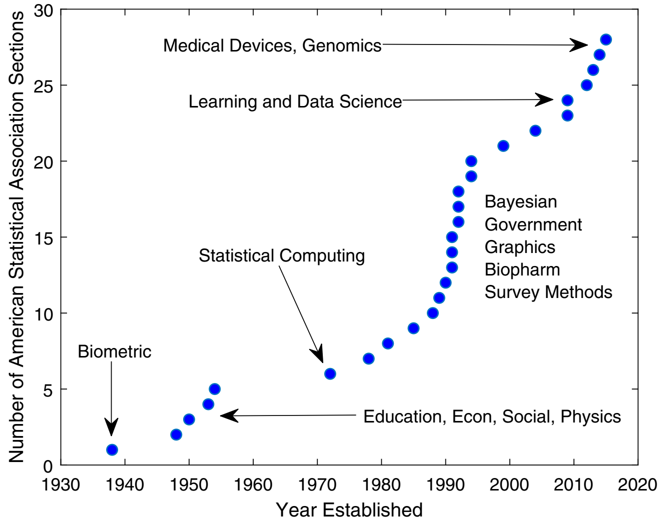

Fig. 3. Timeline shows the year in which sections of the ASA were established. Sections of the ASA focus on specific aspects or applications of statistics when there is significant membership interested in the area, along with the associated mathematical and/or scientific foundation.

Emerging Occupations

In this section, I describe sources of data on occupations in the United States since new and emerging occupations are the main reason why universities develop new programs. Students must have the education and skills needed in the labor force. I first discuss the SOC system and a related occupational framework called the Occupational Information Network (O*NET). I conclude with a discussion of alternative sources of occupational information, such as data from job-posting websites.

SOC System. The federal government first published information on occupations with the 1850 census (15). Early classification systems emphasized the industry rather than the characteristics of the work being performed by the employee. Occupational data were collected on a more frequent basis with the monthly labor force survey (1942), and the Department of Labor published a third edition of their *Dictionary of Occupational Titles* in 1965 (16). Occupation information collected from the census of population were based on data from household surveys and were not readily comparable to data from establishment-based surveys. Further complicating things, the occupation descriptions from the *Dictionary of Occupational Titles* (16) were not easily linked with information from the surveys and census. Thus, the government developed the SOC in 1977, with a revision being reissued in 1980. It is revised periodically. The latest standard will be released in 2018.

The SOC is a federal statistical standard that is used for the collection, analysis, or dissemination of data on occupations. The SOC encompasses all occupations where work is performed for pay or profit. It does not include those occupations that are unique to volunteers. An occupation is classified based on the work that is performed, and it might also be based on the skills, education, or training the employee needs to perform the work. As of the 2010 SOC, there are over 800 detailed occupations. These are combined to form ∼450 broad occupations, 98 minor groups, and 23 major groups.

For the purposes of understanding emerging occupations, it is important to note that some occupations are classified in the "all other" category in a group. This happens when the detailed occupations in a broad group do not account for all of the workers. New and emerging occupations often get classified with this label.

O*NET. The O*NET is a program sponsored by the Department of Labor. The program establishes and maintains a database of occupation descriptions on ∼1,000 occupations in the US economy. The database is publicly available at no cost and is updated continuously.

The latest version is the O*NET 22.3 database and is available for download in several formats under a Creative Commons license (17). Besides occupation titles, the database has characteristics on workers and jobs, as listed here:

- Knowledge, skills, and abilities
- Education, experience, and training
- Interests, work values, and work styles
- Work activities and emerging tasks

The O*NET uses a content model as a framework to identify information about work. This model encompasses aspects of occupations using job-oriented descriptors and people using worker-oriented factors. Job-oriented descriptors include occupational requirements, workforce characteristics, and occupation-specific information (e.g., titles, tasks). Worker-oriented factors include worker characteristics (e.g., abilities), requirements (skills, knowledge, and education), and experience.

The initial O*NET database released in 1998 used occupations from the BLS Occupational Employment Statistics (OES) program. The O*NET program was converted to a taxonomy based on the SOC in 2000, matching the same standard used by the BLS and other agencies. The June 2009 O*NET-SOC database was the third change to the taxonomy and included 153 new occupations based on research in new and emerging occupations. Besides the inclusion of new and emerging occupations, the O*NET-SOC classifies occupations in more detailed levels than the SOC (18) (Fig. 4).

A process was developed by O*NET stakeholders in 2006 to identify, evaluate, and incorporate emerging occupations that are not covered in the O*NET-SOC database. They focused on new occupations created in high-growth industries. The two main criteria they use for identifying new and emerging occupations are as follows: (*i*) significantly different work is performed in the occupation, and (*ii*) it is not represented by the current O*NET taxonomy.

According to the O*NET research, an emerging occupation is one that also has significant employment; has a positive growth rate; has developed because of changes in society, law, or business practices; and has related professional associations and professional publications or journals (19, 20). Note that a new occupation can develop because of changes in technology, which is important for our proposed modeling concept. The BLS has also looked at how one might locate and define emerging occupations. It mentions technological changes as a key driver for the development of occupations, as well as the rise of new industries they are associated with.

OES. The BLS OES program (21) is a rich source of occupational data. The OES gathers data on nonfarm wage and salary workers and publishes estimates of employment and wages for ∼800 occupations. These estimates are available at different levels of geography: the nation, by state, and by metropolitan or nonmetropolitan area. The estimates are also published for over 450 industry groups at the national level.

The OES statistics are published annually based on a full sample of ∼1.2 million establishments. The latest wage and employment information is for May 2016, which was released in the spring of 2017. The OES survey is based on the NAICS industry classification system and the 2010 SOC. The survey samples ∼200,000 establishments semiannually, and it takes 3 y to collect the full sample of 1.2 million respondents. This means that the information collected from the 400,000 establishments

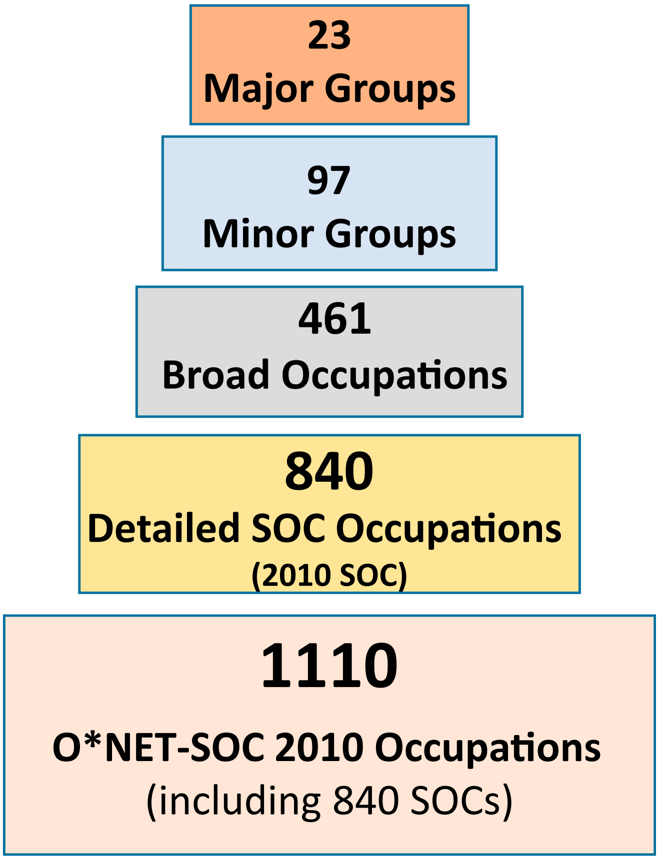

Fig. 4. 2010 O*NET-SOC database includes more occupations than are defined by the SOC. Some of these are new and emerging occupations (18). Reprinted from ref. 17, O*NET Resource Center by the U.S. Department of Labor, Employment and Training Administration (USDOL/ETA). Used under the CC BY 4.0 license. O*NET® is a trademark of USDOL/ETA.

in 1 y is used in the annual estimates over a 3-y period. So, the annual data from the OES do not constitute a time series in a strict sense. However, they could be used to get an idea of changes in nonfarm wage and salary occupations over time.

The OES website at the BLS has data at various geographic levels going back to 1997 (22). Some industry-specific data at the national level only are available for the years 1988–1995.

Job Search Websites. Occupation titles used by employers do not necessarily match those in the SOC, and some of the titles might be indicative of new and emerging occupations. So, it would be interesting to gather data from job search websites over time.

Several job aggregation and analysis companies could serve as potential data sources. Examples include Burning Glass Technologies (https://www.burning-glass.com/), Help Wanted Online from The Conference Board (https://www.conference-board.org/), LinkedIn (https://www.linkedin.com/), Indeed (https://www.indeed.com/), Monster (https://www.monster.com/), and even the US Federal Government job postings at USAJOBS (https://www.usajobs.gov/).

The job postings would have descriptions of the positions, as well as the skills and education required to perform the duties. Job information could be scraped from the web, and text analysis could be used to create a taxonomy. Analyzing this type of data over time could show new and emerging occupations.

Evolution of University Programs

Universities respond to emerging occupations by creating degree and certificate programs needed to train the workforce of the future. The National Center for Education Statistics (NCES) collects data on college degrees and majors. Similar to industries and occupations, the NCES employs a classification system for instructional programs. This is called the Classification of Instructional Programs (CIP) (23). The CIP was first developed in 1980 and was revised four times, with the latest revision occurring in 2010.

The CIP is not intended to duplicate specific majors or fields of study. Instead, it is divided into generic categories in which university programs can be classified. Most of the CIP classes correspond to academic and occupational programs offered at the postsecondary school level. To be included in the CIP, an instructional program must be offered by an educational institution; include more than isolated or unrelated courses; and comprise a set of learning experiences leading to some completion point, such as a degree or certificate.

The detailed categories of the CIP correspond to six-digit codes, and they represent specific instructional programs. They represent the basic unit of analysis when reporting fields of study. There are also four- and two-digit codes.

The 2010 revision of the CIP was accomplished over a 2-y period. One step in its multistage process was to conduct a scan of institutional websites to identify new and emerging programs. This was done, in part, by examining university catalogs, comparing titles and descriptions with the current CIP taxonomy, and determining if differences represent new and distinct areas of study.

An interesting graphic using data from the NCES was created by Quoctrung Bui of National Public Radio (24). This interactive graphic shows college majors from 1970 to 2011, along with their share of degrees awarded over time. One can click on a category to get a timeline for individual overall majors.

Putting It All Together

This proposed conceptual model starts with changes in science and technology over time. These, in turn, drive changes and innovations in industry as companies evolve and take advantage of maturing developments in science and technology. New technologies and processes can potentially produce new jobs or occupations. To remain relevant, universities and educational institutions must develop new programs in response to these new and emerging occupations.

A reviewer of this article rightly pointed out that a viewpoint in this article focuses on new and emerging jobs providing a demand to educational institutions to supply them. This needs to be investigated and supported by evidence and data. To explore these potential connections, one needs data to develop a model of the interactions between developments in science and technology, changes in industry and occupations, and new educational programs. In this article, I have provided information on sources of data for these three main aspects of a potential model, where the availability of data over time was emphasized.

It would be interesting to obtain the historical data, as mentioned, and then to explore the interactions through visualization and network analysis. Exploring the data in this way could provide insights and suggest models to predict emerging occupations.

While not incorporating all aspects of the data sources described in this article, this example hopefully serves to illustrate one approach to discover potentially emerging occupations, which could then be connected to developments in science and technology and changes in educational offerings.

This idea builds on the work of Priebe et al. (25) called quantitative horizon scanning. They explored the idea that scientific breakthroughs and innovations happen when information is combined from disparate fields. In other words, synthesizing ideas across disciplines can produce novel ideas. Priebe et al. (25) developed a log-odds ratio approach to detect when one group is prepared to merge two disciplines, which would result in scientific advancement. The dataset they used was based on research papers and coauthorship graphs.

The concept of quantitative horizon scanning could be applied to job descriptions obtained from job search websites, where each job description is a document and the goal is to detect emerging occupations. If the data are available over time, then one could use this approach to predict occupations we know have recently emerged, such as data scientists.

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