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Detecting Current Job Market Skills and Requirements Through Text Mining

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Peter Nelson was appointed Dean of the University of Illinois at Chicago's (UIC) College of Engineering in 2008. Prior to assuming his deanship, Professor Nelson was head of the UIC Department of Computer Science. In 1991, Professor Nelson founded UIC's Artificial Intelligence Laboratory, which specializes in applied intelligence systems projects in fields such as transportation, manufacturing, bioinformatics and e-mail spam countermeasures. Professor Nelson has published over 80 scientific peer reviewed papers and has been the principal investigator on over $40 million in research grants and contracts on issues of importance such as computer-enhanced transportation systems, manufacturing, design optimization and bioinformatics. These projects have been funded by organizations such as the National Institutes of Health, the National Science Foundation, the National Academy of Sciences, the U.S. Department of Transportation and Motorola. In 1994-95, his laboratory, sponsored by the Illinois Department of Transportation, developed the first real-time traffic congestion map on the World Wide Web, which now receives over 100 million hits per year. Professor Nelson is also currently serving as principal dean for the UIC Innovation Center, a collaborative effort between the UIC Colleges of Architecture, Design and the Arts; Business Administration; Medicine and Engineering.

Detecting Current Job Market Skills & Requirements Through Text Mining

Recent research exists that utilizes machine learning techniques to analyze the underlying patterns in the job market. In this paper, Skill Miner System (SMS) is presented. SMS utilizes text mining algorithms to identify these skills and qualifications employers seek for in STEM fields. In addition, SMS generates a skill demand index (SDI), which is used to determine the demand for particular skills. This study focuses on Industrial Engineering but can be easily adaptable to other fields.

*Data for this study was collected by scrapping various job postings for Industrial Engineers. The data used to develop SMS consisted of more than 5,000 jobs. The underlying pattern of the job market is compared to a public database of various occupational information, O*NET. O*NET, sponsored by the U.S. Department of Labor, is one of the most comprehensive publicly accessible databases of occupational requirements for skills, abilities and knowledge. However, by itself the information in O*NET is not enough to characterize the distribution of occupations required in a given market or region.*

*SMS is different from O*NET as it detects skills required in the job market on a more frequent basis and provides a metric to determine the importance of a skill. This paper shows that SMS is able to detect skills that are required by the job market and are not mentioned in O*NET. SMS sets a weight to portray the demand for each skill. This is beneficial for institutions and organizations to remain competitive in the job market.*

At the University of Illinois at Chicago, senior engineering undergraduates in the Department of Mechanical and Industrial Engineering are required to take a professional development course (PDC) to assist in their career development. PDC employs SMS routinely to help each student cater to various job positions. In addition, resumes are improved by using additional relevant keywords employers seek, which are detected by SMS. SMS has assisted in increasing the number of students that graduate with a job offers and in the course's goal of helping students obtain careers.

The analysis presented in this paper shows that SMS can benefit various stakeholders, such as universities, students, employers, and recruiting firms. Universities will have a better understanding of the job market and will be able to improve the education of their students with the evolving job market. Students will be more qualified and better prepared for the job market. Employers and recruiting firms will be able to remain competitive in the job market.

I. Introduction

Problem Description

Since 1950, the demand for science, technology, engineering, and mathematics (STEM) occupations have been growing rapidly. The skills required for each occupation are changing. The main objective of this paper is to introduce a tool called Skill Miner System (SMS) that is used to produce a snapshot of what Industrial Engineering's in-demand skills look like. SMS may also be used to track the trends of these skills. SMS will benefit various stakeholders, such as universities, students, employers and recruiting firms. The authors show the application of SMS at The University of Illinois at Chicago (UIC) and present the easy adaptation to other fields of engineering. UIC and additional universities can have a better understanding of the job market using SMS. They will be able to transform their curriculum to better suit the demand of the job market. Students will be more aware of the demands of the job market. Employers and recruiting firms can use the list of skills to remain competitive in the job market.

Motivation

The demand for skilled workers is growing while the desired skill set in engineering occupations is changing rapidly. The ability to adapt to the dynamic skill requirements is key to the success of an individual's career. It is essential for job seekers to be aware of skills that will allow them to obtain and perform within an occupation.

Engineering students are prepared to tackle their fields through the rigorous educational training provided by their universities. The education of engineers follows a structured curriculum consisting of mathematics, physics, and core engineering courses. These courses provide skills deemed necessary for engineers. However, these skills might not cater to the requirement of the job market. It is imperative to properly develop and teach the necessary skills for the workforce to each engineering student since a degree is no longer a guarantee of a good job [1]. Each of these students need to be prepared for what the industry may expect of their skillset [2]. It is therefore beneficial for students and universities to be aware of the skills required by the job market.

Several topics of research are available indicating the importance of integrating various skills from the job market into the engineering curriculum. Chikumba, S. et al. discusses the benefit of integrating hard technical skills and technologies with the soft skills required by Industrial Engineers to satisfy the marketplace [3]. The University of Florida produced a study on the "talent paradox" in which students cannot find jobs because they do not possess the skills required by companies and companies cannot find the right employees because of the lack of skills in applicants [4]. One article outlines a course for engineering students in their last semester. This course aims to bridge the skills gap from school to real life situations [5],[6]. The U.S. Department of Labor provides a publicly accessible database for skills, abilities, and knowledge required for various occupations through its online website, O*NET [7]. The skill list provided by O*NET does not characterize the distribution from the current job market. However, this further exemplifies the necessities for emerging graduates to be aware of the skills in high

demand. These in-demand technical and professional skills can be acquired through coursework and are necessary for the career success of engineering graduates.
In this paper, a set of technical and professional skills required by the job market for Industrial Engineers is proposed. The skill set is an output of SMS. The remaining sections of this article are as follows. Section II provides a literature review of the key concepts used in the study. Data collection will be presented in Section III. Section IV will hold the methodology for identifying the set of high demand skills for Industrial Engineering graduates. Experiment and results will be presented in Section V. Lastly, the conclusion will be presented in Section VI.

II. Literature Review

Industrial Engineering

This paper looks at applying SMS to the field of Industrial Engineering. As stated by the United States Bureau of Labor Statistics [8], Industrial Engineers develop efficient systems that integrate machines, workers, information, materials and energy to create a product or to provide a service. Identifying the skills that are in demand for this field's prospective industries is of utmost importance due to the adaptive and versatile nature of this specific engineering discipline. Traditional skills that are taught throughout the education of Industrial Engineering students include topics and technologies such as: Linear and Non-Linear Programming, Discrete Event Simulation, Work Productivity Analysis, and Statistical Quality Control. These are a selected set of skills summarized from leading Industrial Engineering Bachelors of Science programs [9]–[11] . These topics are covered across the Industrial Engineering curriculum while following the guidelines of the Accreditation Board for Engineering and Technology, Inc. (ABET) [12], [13]. ABET is a non-profit entity that accredits engineering programs by setting a minimum for which courses should be offered to somewhat standardize a bachelor programs curricula [14]. Passow, HJ et al. published a study on which ABET competencies engineering graduates find most useful once they enter the workforce [15]. Additional skills and expectations for Industrial Engineering can also be researched through the Occupational Information Network (O*NET) [7].

Occupational Information Network

O*NET is the United States' leading free online database for occupations. It summarizes relevant information, such as expected skills and median salaries, for various occupations [7]. The website describes the history and origins of the O*NET project as it was developed through a sponsorship from the United States Department of Labor/Employment and Training Administration (USDOL/ETA). The O*NET database houses more than 1,000 occupations in the U.S. economy. Each of these occupations is accompanied by hundreds of descriptors and statistics, which are collected from the Bureau of Labor Statistics [7].

One of the key features of the O*NET online website is for students to discover occupations of interest. Students may take assessments from their own computers (Interest Profile and Work Importance Profiler) to help them narrow down their interests [16], [17]. From this point on, they can view the educational requirements and skills necessary for that field. It is essential to understand the important attributes of the O*NET online system in order to understand the significance of research projects involving the system [18], [19]. Any study with the goal of improving or supplementing O*NET, such as this paper, would potentially provide critical information towards graduating Industrial Engineering students.

Educational Data Mining & Text Mining

Educational Data Mining (EDM) is the use of data mining in the field of engineering education. EDM has produced many research studies and publications, as evident by the numerous surveys available [20]–[23]. A few of the topics within EDM include intelligent tutoring systems, predicting student retention, and Knowledge Discovery in Databases (KDD)[24]. One popular area of data mining and emerging into EDM is text mining.

Text mining is knowledge discovery using databases that are textual. The process generally involves extracting patterns and knowledge from unstructured text data [25]. Unstructured text data can be gathered using web scraping or employing APIs [26]. Similar to data mining, there is a vast amount of survey information that explore the applications and techniques of text mining [27], [28]. Not much research has been published in the realm of using text mining and web scraping for applications including jobs and skills. One similar application of text mining was a study conducted on 200 job applications and surveys to analyze the skills necessary for systems analysts to be successful in their jobs [29]. A more in-depth web scraper collected and analyzed the skills from 15,000 Information Technology jobs [30]. This study uses both web scraping to collect job posting data and text mining to extract knowledge about in-demand skills in Industrial Engineering. An overview of web crawlers is provided in [31].

In Section III, the details of the data collection for this project are explained. In Section IV, the methodology for converting the collected data to skill keywords is discussed. The details of the conducted experiments as well as the obtained results related to Industrial Engineering technical and professional skills sets based on the current snapshot of the job market are described in Section V. The paper is concluded in Section VI.

III. Data Collection

Initially, information is gathered about Industrial Engineering jobs to conduct this study. This information is available in the form of online job postings. Companies from every field can easily advertise their available positions by creating a job posting on sites such as Indeed, Monster, and CareerBuilder [32]–[34]. Postings typically include information such as the company name, position title, company background, position requirements, and preferred qualifications.

While the required information is openly available for anyone to see, retrieving this information in a clean format is an issue. To extract information, an automated script (web crawler) is utilized to extract information from specific job boards. There are services available to extract these pieces of information for those who do not have the capability of creating their own web crawler. Examples of these services include Web Scraper [35] and Crawly [36]. In this project, a web

crawler was created using the BeautifulSoup library in Python [37]. BeautifulSoup (BS) allows the user to easily extract the HTML of a provided webpage.
To obtain these jobs, the base URL was concatenated with the keywords of interest. This translates to 'https://www.careerbuilder.com/jobs-industrial-engineer' for Industrial Engineering jobs on CareerBuilder. BS is then used to extract the HTML of this URL and obtain the number of pages of the search. With the number of pages, BS can be used to loop over the pages of 'https://www.careerbuilder.com/jobs-industrial-engineer?page_number=XX' where XX goes from 1 to the total number of pages. The web crawling process is illustrated in Figure 1.

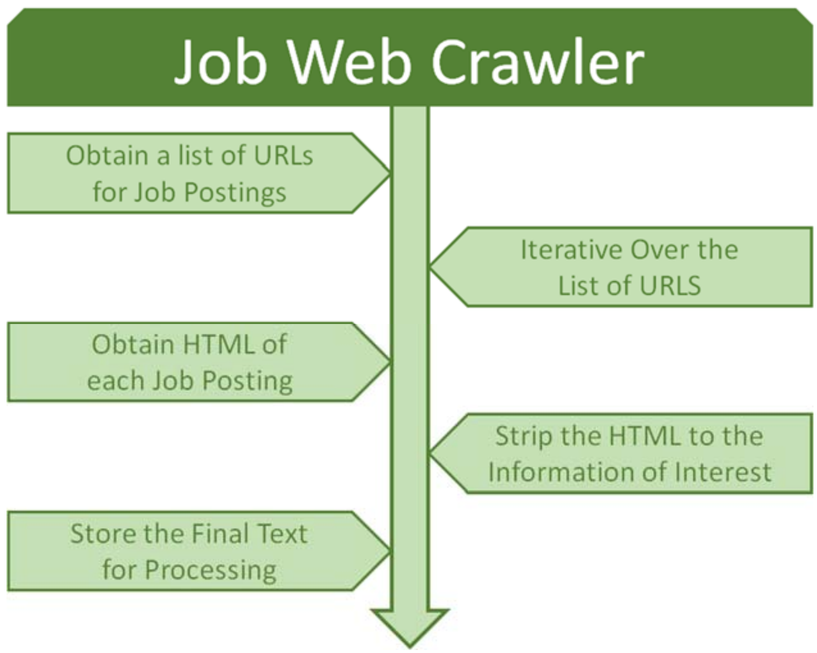

Figure 1: Summary of how jobs are collected online

Before extracting a jobs HTML, the script verifies that the job is not in the current database. This verification is done using the unique Job ID found in the job posting. This verification has the potential to miss duplicate jobs that do not have the same Job ID. An example of a missed duplication is when the same job is posted twice with unique job IDs. For each posting the job title and location are extracted.

Every page has links to job postings that can be extracted from their HTML. Then the posting information is stripped down to just the main elements. These elements include Job Description, Job Requirements, and Qualifications. The stripping process aims to remove text that is not relevant to the task of skill extraction. Information that is stripped away includes company information, additional page contents, and anything else that does not have the potential to list skills or knowledge required for the position.

For the data collection, the final dataset for this study consists for over 5,000 unique Industrial Engineering jobs. The timeframe for when this data was gather was between November 2017 and January 2018. The time for data collection represents a snapshot. This method can represent a trend when used consistently over a longer period of time. These jobs are all collected from CareerBuilder. This is because CareerBuilder posts jobs in a similar format, making the task of stripping the text to just relevant information reliable. It is possible to use jobs from other boards including Indeed and Monster, however; the stripping process would be more complicated.

IV. Methodology

The project methodology is broken down into two phases. Phase 1 is used to extract keywords and phrases from the job descriptions. Phase 2 provides a more detailed analysis of the skills that are extracted from postings. This two-phase methodology is illustrated in Figure 2. The methodology will not be able to capture trivial skills and skills that are so evident that they are not mentioned in the job postings. Inferring these skills are extremely difficult to capture, and a reason why this tool should be used alongside O*NET.

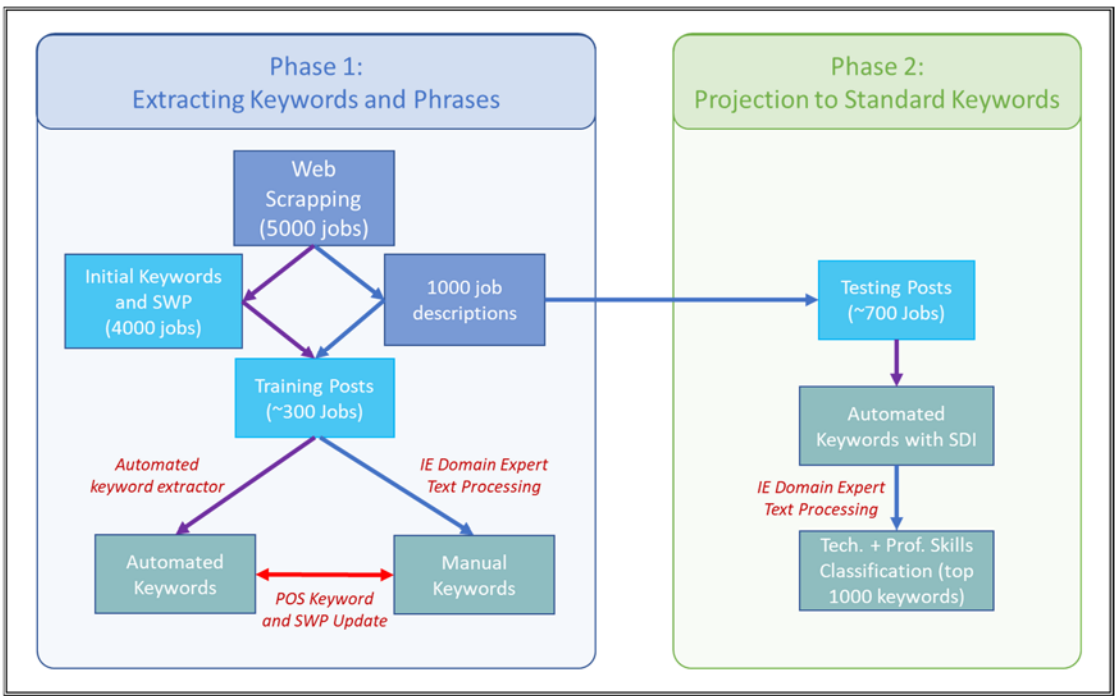

Figure 2: Methodology of how technical and professional skills are generated

Phase 1: Extracting Keywords and Phrases

Extracting accurate keywords and phrases requires an iterative process. Initially, keywords are defined as nouns and phrases as a chunk or sequence of nouns. Approximately 4,000 job postings are used to extract these keywords and phrases. The NLTK package is utilized in Python to extract keywords [38]. This package is also used to parse the text into the syntactical parts of speech (POS). Given the POS breakdown, text can be analyzed to extract phrases in the job posting that convey the skills of interest. To support Phase 1, an Industrial Engineering domain expert is used to identify keywords and phrases that are not skills required by an engineer. This set of keywords and phrases are identified as stop words or stop phrases (SWP). The SWP are words and phrases the system will ignore at the next iteration. Examples of SWP are: “today”, “jobs”, “someone”.

At the beginning of the next iteration, an Industrial Engineering domain expert extracts professional and technical skills required by 5 jobs. SMS then extracts keywords and phrases defined. Once the keywords and phrases are detected, the SWP list is used to remove keywords and phrases that are not skills required by an engineer. At this stage, the keywords and phrases extracted by the system is compared to the list created by the Industrial Engineering domain expert. The POS of the keywords and phrases that were not extracted are then used to update the definition of keywords and phrases. Based on these 5 jobs, the SWP list is also updated. This process is iterated until about 300 jobs are completed. This is when the POS definition of a keyword and phrase converges. In other words, at this stage, most of the professional and technical skills from a job posting are extracted. It should be noted, the SWP list does not converge. A list of keywords that are not professional and technical skills required by an Industrial Engineer are still obtained.

Phase 2: Projection to Standard Skills

During Phase 2, the system is applied on approximately 700 jobs, all Industrial Engineering jobs collected on January 14th, 2018. The system also outputs the frequency of the keywords and phrases in all the jobs. The frequency of a keyword, i, is standardized, using equation (1), between 0 and 1 to form the skill demand index, SDI.

$$SDI_i = \frac{frequency_i - \min(frequency)}{\max(frequency) - \min(frequency)} \tag{1}$$

The higher the SDI, the more frequent a word or phrase is. The higher the SDI is, the more demand that particular skill has. Once the SDI is generated, the top 1,000 keywords and phrases from the 700 jobs are used by an Industrial Engineering domain expert who categorizes them. The expert referred to in Phase 1 and Phase 2 has been in the field of Industrial Engineering for over twenty years in both industry and academia. He has been involved, as a leader or a team member, in more than 70 industry projects in almost every area that is recognized by the universities in the United States related to the Industrial Engineering field. The areas include but not limited to Safety Engineering, Ergonomics, Facilities Planning, Logistics and Supply Chain, Quality Control, Manufacturing, Construction, Financial Decision Making, Education, Healthcare, and Project Management. He has applied different techniques including Operations Research, Simulation, Data Mining and Machine Learning, Lean Management, and Statistics in these projects. The expert does not categorize the keywords based on his personal beliefs about Industrial Engineering related jobs. He uses his industry and academia experience to select and categorize the keywords. In his selection and classification of the keywords, he only excludes the keywords that are absolutely unrelated to Industrial Engineering not based on his personal belief but based on his history of interaction with other experts in academia and industry. Therefore, the list includes keywords that might not be acceptable to the expert as an Industrial Engineering keyword but are recognized by at least one other individual with whom the expert has interacted through his professional life.

The Industrial Engineering domain expert goes through the top 1,000 keywords and phrases to manually categorize the keywords into various skills and SWP. There are instances where keywords and phrases are synonymous with other keywords and phrases. In these cases, the keywords and phrases are categorized into one category. For example, “C++”, “cad”, “C”, “R”, are all categorized as “programming knowledge and software”. Another example, “teamwork” and “work in a team” are categorized into a professional skill, “teamwork”.

Once this is completed, the expert classified the various skills as a professional skill or a technical skill. A technical skill is a skill that is specific to the degree. An example of a technical skill for Industrial Engineering is “plant and facilities layout”. A professional skill is a career skill that is not a coursework specific to the degree. An example of a professional skill is “communication skill”.

V. Experiments & Results

The top 25 technical skills and top 12 professional skills are summarized in Table 1. The categorization of skills into technical or professional was made by the authors, research, and the expert’s opinion. Technical skills were defined as skills related to the field of Industrial Engineering or skills which are traditionally taught. An example for technical skills is Lean/Six Sigma because it is a skill that shows up in many job postings and is found in the Industrial Engineering Curriculum often. A professional skill is defined as a skill generally learned and developed through job experience, such as team work and communication. It is important to note that the list generated by this study may not be a complete list of skills for Industrial Engineers. However, it is based on the previously mentioned expert’s opinion and is regarded as a fair representation of the current role of the major. Based on the available postings in this specific date, “Safety and Quality” was the most essential technical skill an Industrial Engineer needed to have. “Communication skills” was the most sought for professional skill. The common programming languages and software skills an Industrial Engineer needed to have were the following: (1) AutoCAD, (2) R, (3) CAD, (4) SAP, (5) C, (6) SolidWorks, (7) SAS, (8) Python, (9) Java, (10) C++, (11) CMMS.

As can be noticed, the system that is provided and list of keywords that are detected are dynamic and can be updated daily. In comparison, O*NET is not able to do so. O*NET provides a comprehensive set that encompasses most of the skills detected by the system. O*NET does require an Industrial Engineer the knowledge of “SolidWorks”, “SAS”, “C”, and “CMMS”. Contrastingly, there are a few software skills mentioned in O*NET that are not mentioned in the analyzed jobs by SMS. Some of these software skills are “StatMost”, “IGESworks”, and “Hewlett Packard LoadRunner”. According to O*NET, “Hewlett Packard Load Runner” is a “hot technology” and is “frequently included in employer job postings”. Yet, no jobs postings from all 5000 job postings (4300 from phase 1 and 700 from phase 2) contained “Hewlett Packard Load Runner”.

Table 1: The top 25 technical skills and top 12 professional skills extracted by SMS

Technical Skills	SDI	Professional Skills	SDI
safety and quality	1.00	communication skills	0.43
manufacturing	0.56	reports	0.20
machine and equipment	0.39	customer service	0.12
programming languages & software	0.38	teamwork	0.12
engineering drawings	0.28	asset life	0.07
finance and accounting	0.24	writing	0.03
supply chain	0.18	consulting	0.02
project management	0.17	multi-task	0.02
data collection and analysis	0.16	leadership skills	0.02
plant facilities and layout	0.15	interpersonal skills	0.02
product and technical designs	0.15	solving skills	0.02
construction	0.15	decision making	0.01
process improvement	0.14		
energy and industrial markets	0.12		
parts and assemblies	0.12		
scheduling	0.11		
equipment installation	0.10		
work and purchase orders	0.10		
electrical and mechanical troubleshooting	0.09		
industrial automation	0.09		
fabrication	0.09		
marketing	0.08		
clean energy	0.07		
environment and infrastructure	0.07		
hydraulics and pneumatics	0.06		

Furthermore, O*NET does not mention the following skills from Table 1: “safety”, “finance and accounting”, “plant facilities and layout”, “construction”, “process improvement”, “energy and industrial markets”, “work orders”, “electrical and mechanical troubleshooting”, “hydraulics and pneumatics”, “industrial automation”, “marketing”, “asset life”, and “decision making”. These are all professional and technical skills that appeared in several jobs.

The SDI provided by SMS gives a better understanding of skills that are highly in demand. The maximum and minimum frequency in the set of keywords and phrases is 1854 and 1 respectively. Since “safety and quality” has a frequency of 1854, its SDI is 1. On the other hand, “hydraulics and pneumatics” has a frequency of 119, yielding to a SDI of 0.06. Therefore, the technical skill “safety and quality” has a higher demand than “hydraulics and pneumatics” as the SDI of “safety and quality” is 17 times greater than “hydraulic and pneumatics”.

Stakeholders that can benefit from the results of this study are the various engineering programs, their students, faculty, and administrators. From the top 25 technical skills, “hydraulics and pneumatics”, “construction”, “energy and industrial markets”, “equipment installation”, “work and purchase orders”, “electrical and mechanical troubleshooting”, “fabrication”, “marketing”, “clean energy”, and “environment and infrastructure” are not incorporated in the core curriculum of the University of Illinois at Chicago (UIC). Therefore, the Industrial Engineering program at UIC is considering to either create elective courses in such areas or to allow their students to take courses from other programs that provide courses covering these skill areas.

Currently, the graduating students from the Industrial Engineering program at UIC are using the list of technical and professional skills derived by SMS through multiple means. The list of technical and professional skills is provided in a professional development course (PDC) for graduating seniors. The objective of this course is to assist the career development of Industrial Engineering students. PDC utilizes these skills to improve resumes of its students by reminding them projects they have completed while using better keywords in their resume. In addition, PDC provides the list of in-demand technical and professional skills to enhance their job seeking experience.

Table 2 shows an application of the tool. The table is a portion of what is provided to the students taking PDC. The Industrial Engineering courses provided at the school are listed alongside two columns generated from results of this study: Applied Software and Related Job Positions. Applied Software and Related Job Positions show students the tools and jobs relevant to those courses. For example, the course called Financial Engineering (IEX1) in the second row of Table 2 covers techniques (listed in the third column) such as present worth analysis, annual worth analysis, etc. The software tools (listed in the fourth column) learned in this course are Excel and R. Students who plan to apply to the position in the last column can list any of the keywords listed in columns 3 and 4 in their resume. It should be mentioned that not all the keywords listed in Table 2 directly exist in Table 1. Some of the keywords in Table 2 are generated from the breakdown of the keyword categories listed in Table 1.

Table 2: Industrial Engineering course descriptions with their applied software and related jobs

Course Code	Course Name	Major Skills/Techniques Learned	Applied Software	Related Job Positions
IE 201	Financial Engineering	Mathematical formulas for representing the time value of money, Present worth analysis, Annual worth analysis, Rate of return analysis, Benefit/cost analysis and public sector economics, MARR, Replacement and retention decisions, and more	Excel, R	Financial Analyst, Project Manager, Acquisitions Manager, Finance Manager, Portfolio Manager, Real Estate Manager, Operations Analyst, Industrial Engineer, Consultant, Risk Manager
IE 342	Probability and Statistics for Engineers	Sample space, Permutations, Probability of an event, Additive rules, Conditional probability, Bayes' rule, Discrete, continuous, and joint probability distributions, Mean, variance, and covariance of random variables, and more	Excel	Operations Manager, Manufacturing Engineer, Analyst, Continuous Improvement Manager, Bioinformatics, Environmental Statistics, Health Systems Engineer, Epidemiologist, Quantitative Analyst
IE 345	Regression Applications and Forecasting in Engineering	Various Time-Series analysis techniques used to extract meaningful characteristics of data. Simple regression analysis, Multiple regression analysis, Exponential smoothing, Winter's method for exponential smoothing, Box-Jenkins methodology: Non-seasonal & Seasonal models	Excel, R, Python	Business Analyst, Logistics Manager, Supply Chain Manager, Operations Manager, Data Scientist, Data Analyst, Cost Analyst, Quality Assurance Analyst, Health Systems Engineer, Transportation Manager
IE 365	Work Productivity Analysis	Quantitative analysis of work, Time studies, Performance allowances and ratings, Compute learning curves, parameters and develop new standards, Wage payment and incentive Plans, Work sampling, Operations analysis tools, Ergonomic analysis, Workstation design, Formula construction.	Excel, R, PowerPoint	Lean Manager, Operations Manager, Productivity Analyst, Labor Analyst, Project Manager, Manufacturing Engineer, Health Systems Engineer
IE 380	Manufacturing Process Principles	Introduction to basic manufacturing processes (casting, bulk deformation, metal cutting, material interaction). Economics of a manufacturing processes, and more.	SolidWorks, Excel, PowerPoint	Manufacturing Engineer, Mechanical Engineer, Materials Engineer, Industrial Engineer

VI. Conclusion

In this paper, a set of technical and professional skills currently in-demand for an Industrial Engineer are presented. In addition, a dynamic system that can extract technical and professional skills from current job postings is proposed. SMS should be used as a supplement to O*NET; as O*NET contains skills that are not available in the postings. An SDI is utilized to measure the frequency of skills that occur in job postings on a given day. The SDI indicates the demand for a particular skill. Currently, the technical and professional skills are utilized in a professional development course. The Industrial Engineering program at the University of Illinois at Chicago will utilize this system by providing electives that teach skills for in-demand topics.

The system and set of skills have a positive impact on various stakeholders, such as universities, students, employers, and recruiting firms. However, the system has plenty of room for improvement. Further research needs to be done to reduce the number of stop words or phrases generated at each iteration. Moreover, further studies can be done to monitor trends in skills in the job market over a period of time.

References

[1] J. Jones and J. Schmitt, "A college degree is no guarantee," *Center for Economic and Policy Research* (CEPR) 2014.

[2] Bernd Schulz, "The Importance of Soft Skills: Education beyond Academic Knowledge," *Journal of Language & Communication*, 2008.

[3] S. Chikumba, "Development of soft engineering skills for industrial engineering technologists through effective mentoring," *WACE 17th World Conference on Cooperative & Work-Integrated Education*, 2011.

[4] H. Rao, *Workers Can't Find Jobs, Jobs Can't Find Workers: Solving the Talent Paradox*., Lynn University, 2015.

[5] H. Darabi, E. Douzali, F. S. M. Karim, S. T. Harford, and H. Johnson, "Life after university for engineering graduates," in *ASEE Annual Conference and Exposition*, Conference Proceedings, 2017, vol. 2017–June.

[6] M. Loftus, "Real World 101", *ASEE PRISM*, pp. 34-37, Dec-2017.

[7] O*Net, "O*NET Online." [Online]. Available: https://www.onetonline.org/. [Accessed: 25-Jan-2018].

[8] Bureau of Labor Statistics, "Industrial Engineers," Bureau of Labor Statistics Occupational Outlook Handbook, 2016. [Online]. Available: https://www.bls.gov/ooh/architecture-and-engineering/industrial-engineers.htm. [Accessed: 25-Jan-2018].

[9] UIUC, “Industrial Engineering Degree | Department of Industrial and Enterprise Systems Engineering | Illinois,” University of Illinois at Urbana Champaign, 2017. [Online]. Available: https://ise.illinois.edu/undergraduate/industrial-engineering-degree/. [Accessed: 25-Jan-2018].

[10] UMich, “BSE Programs and Curriculum – Industrial and Operations Engineering,” University of Michigan, 2017. [Online]. Available: https://ioe.engin.umich.edu/academics/undergrad/programs/. [Accessed: 25-Jan-2018].

[11] GATech, “Bachelors of Science in Industrial Engineering | Georgia Institute of Technology | Atlanta, GA,” Georgia Institute of Technology, 2017. [Online]. Available: https://www.isye.gatech.edu/academics/bachelors. [Accessed: 25-Jan-2018].

[12] R. M. Felder and R. Brent, “Designing and Teaching Courses to Satisfy the ABET Engineering Criteria,” *Journal of Engineering Education*, vol. 92, no. 1, pp. 7–25, Jan. 2003.

[13] L. J. Shuman, M. Besterfield-Sacre, and J. McGourty, “The ABET ‘Professional Skills’ - Can They Be Taught? Can They Be Assessed?,” *Journal of Engineering Education*, vol. 94, no. 1, pp. 41–55, 2005.

[14] ABET, “Accreditation Board for Engineering and Technology, Inc.,” 2017. [Online]. Available: http://www.abet.org/. [Accessed: 03-Feb-2018].

[15] H. J. Passow, “Which ABET Competencies Do Engineering Graduates Find Most Important in their Work?,” *Journal of Engineering Education*, vol. 101, no. 1, pp. 95–118, Jan. 2012.

[16] “O*NET Resource Center - Work Importance Locator (WIL) and Work Importance Profiler (WIP),” O*NET. [Online]. Available: https://www.onetcenter.org/WIL.html?p=3. [Accessed: 25-Jan-2018].

[17] O. Software, “O*NET Interest Profiler at My Next Move.” [Online]. Available: https://www.mynextmove.org/explore/ip. [Accessed: 25-Jan-2018].

[18] N. Peterson, M. Mumford, “Understanding work using the Occupational Information Network (O* NET): Implications for practice and research,” *Personnel Psychology*. 2001.

[19] M. Cifuentes and J. Boyer, “Use of O* NET as a job exposure matrix: a literature review,” *American Journal of Industrial Medicine*., 2010.

[20] C. Romero and S. Ventura, “Educational data mining: A survey from 1995 to 2005,” *Expert Systems with Applications*., vol. 33, no. 1, pp. 135–146, 2007.

[21] R. Baker and K. Yacef, “The state of educational data mining in 2009: A review and future visions,” *JEDM Journal of Educational Data Mining*, 2009.

[22] R. B. Sachin, “A Survey and Future Vision of Data mining in Educational Field,” *Advanced Computing & Communication Technologies*, 2012.

[23] C. Romero, “Educational data mining: a review of the state of the art,” *IEEE Transactions on Systems, Man, and Cybernetics*, 2010.

[24] D. B. Fernandez and S. Lujan-Mora, “Comparison of applications for educational data mining in Engineering Education,” in *2017 IEEE World Engineering Education Conference (EDUNINE)*, 2017, pp. 81–85.

[25] A.-H. Tan, “Text mining: The state of the art and the challenges,” in *PAKDD 1999 Workshop*, 1999.

[26] S. Munzert, C. Rubba, P. Meißner, and D. Nyhuis, *Automated data collection with R: A practical guide to web scraping and text mining*. John Wiley & Sons, 2014.

[27] M. Sukanya and S. Biruntha, “Techniques on text mining,” in *2012 IEEE International Conference on Advanced Communication Control and Computing Technologies (ICACCCT),* 2012.

[28] V. Gupta and S.L. Gurpreet, "A survey of text mining techniques and applications." *Journal of emerging technologies in web intelligence* 1.1, 2009.

[29] E. Karanja, D. M. Grant, S. Freeman, and D. Anyiwo, “Entry level systems analysts: What does the industry want?,” *Informing Science: The International Journal of an Emerging Transdiscipline,* 2016.

[30] L. Thiele, “Careerlink skills: Analyzing IT skills from online job postings,” *AIM*, 2014.

[31] M. Kumar, R. Bhatia, and D. Rattan, “A survey of Web crawlers for information retrieval,” *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 2017.

[32] “Indeed,” 2018. [Online]. Available: https://www.indeed.com/.

[33] “Monster,” 2018. [Online]. Available: https://www.monster.com/.

[34] “CareerBuilder,” 2018. [Online]. Available: https://www.careerbuilder.com/.

[35] “Web Scraper,” 2017. [Online]. Available: http://webscraper.io/. [Accessed: 01-Feb-2018].

[36] “Crawly.” [Online]. Available: http://crawly.diffbot.com/. [Accessed: 01-Feb-2018].

[37] L. Richardson, “Beautiful Soup 4.4.0 documentation.” [Online]. Available: https://www.crummy.com/software/BeautifulSoup/bs4/doc/. [Accessed: 01-Feb-2018].

[38] S. Bird and E. Loper, “NLTK,” in *Proceedings of the ACL* 2004, p. 31, 2004.