Developing a Data-Driven Emerging Skill Network Analytics Framework for Automated Employment Advert Evaluation

Xiaoming Liu
xliu@semo.edu
Department of Computer Science

Dana Schwieger
dschwieger@semo.edu
Department of Management

Southeast Missouri State University
Cape Girardeau, MO 63701 USA

Abstract

Rapid advancements and emergent technologies add an additional layer of complexity to preparing computer science and information technology higher education students for entering the post pandemic job market. Knowing and predicting employers' technical skill needs is essential for shaping curriculum development to address the emergent skill gap. Examining online advertisements to determine the skills sought by employers of new hires for these emerging areas and ensuring that program course content addresses these skills can be a daunting task. In this paper, the authors describe the development of a data-driven analytics framework that can be used for evaluating emerging skill clusters in online job adverts and the application of the framework to a mobile computing course at the authors' institution.

Keywords: Graph mining, network clustering, time-evolving network, emerging technology skills analysis framework

1. INTRODUCTION

In light of the current technology knowledge explosion, rapid advancements and continuous innovations require various actors (students, employers, educators, etc.) to quickly adapt in order to stand at the forefront of the competitive edge (Mitchel, 2022; Sun, et al., 2021;). In order to fill the "Skill Gap" left in the wake of these advancements, information systems (IS) educators must be able to understand and incorporate emerging information technology (IT) innovations to prepare students for future success (Agarwal & Ahmed, 2017; Mitchel, 2022). Meeting industry demand for such highly dynamic technical skills provides a significant challenge for IS educators (Leidig et al., 2020; Mitchell, 2022). The accelerated digital transformation of higher education institutions associated with new online platforms, tools, and teaching modalities wrought by the COVID-19 epidemic adds additional challenges to effectively evaluating current online learning content and meeting the needs of the job market (Alenezi, 2021).

In recent years, online job advert-derived analytics solutions for skill demand assessment have been developed and implemented (Sun, et al., 2021; Tamašauskaitė & Groth, 2022). Likewise, researchers have adopted data-driven analytics approaches to assessing IS/IT courses and curriculum (deBlas, et al., 2021; Yu, et al., 2021). Nevertheless, a quantitative framework is lacking for effectively assessing the emerging technology-related learning content in IS/IT courses through combining up-to-date and more accessible online job advert analytics with online course content analytics.

In this paper, the authors proposed a data-driven emerging skill network analytics framework combining online job advert analytics with online course content analytics for automated knowledge interaction evaluation in IS/IT courses. Through applying the proposed analytics framework, students are able to maximize their skill value in the job market. IS/IT educators are also able to provide adaptive and up-to-date learning content relative to the current job market demand. Furthermore, employers may use the skill-centric skill assessment to recruit and retain skilled talents. The proposed framework consists of a conceptual university-industry knowledge interaction model, online job advert analytics module, and an online course content analytics module for automated knowledge interaction evaluation in IS/IT curriculum. More specifically, the framework extracts graphlets with local-topological statistics from generated skill networks for role-based skill interaction analysis. A case study in an online mobile application development course was implemented for proof of concept and early verification.

2. RELATED WORKS

Identifying information technology job skills sought by employers has long been of interest to job seekers, academes, human resource administrators, and many others (Cummings & Janicki, 2020; Koong, Liu, & Liu, 2002; Morris, Fustos, & Haga, 2018). Research has been conducted using data mining and valuation models to identify and value skills in online job adverts (Sibarani & Scerri, 2020a; Smith & Azad, 2014). Further, technology innovations and the related emergent skill sets are fostered by the symbiotic relationship between education, research, and industry. To address the rapid evolution of technology development in the industrial space, it is imperative that universities develop support practices for gaining insights.

Knowledge Interaction

Cowan and Jonard (2001) noted that "…there are two aspects to technical change: knowledge creation and knowledge diffusion." They recognized the value of networks in the knowledge creation and diffusion process as both collective successes and failures are shared, processed, and examined by members of the sharing network. In his study of network epistemology, Zollman (2013) acknowledged the value generated by groups in knowledge development and transfer. His study focused on the particular nuances of the communication processes within these networks. Wijesinghe (2022) described the importance of collaborative relationships between educational institutions, research and development entities, industrial players, and innovation intermediaries (e.g., fellows, incubators, development agencies, etc.) in the development and transfer of technology innovations. Such relationships are essential to expeditious development and transfer of tacit, implicit, and explicit knowledge. da Silveria Bueno, et. al (2021) observed that global developments in the bioenergy field have been fueled by such collaborative networks. The authors noted that "…knowledge flows from the emerging networks and their relationships are outlining the frontier technologies in the bioenergy paradigm (p. 15)." Advancements in bioenergy production and other scientific fields illustrate how invaluable interdependent networks are to dynamically developing fields, technical organizations, and programs of study wishing to stay at the forefront of their fields.

Skill Network Analysis

Researchers have taken multiple approaches to addressing the volume and variety of network data. de Blas, et. al, (2021) proposed the use of network analysis and dependency graphs in the design and development of undergraduate curriculum to reflect the temporal sequencing and dependencies of course content and its acquisition. The authors indicated that identifying key nodes and their relationships was one of the most important issues in the process.

To address the widening skill gap found in the European data economy between supply and demand, Sibarani and Scerri (2019) used hierarchical clustering with co-word occurrence to identify job skill advert network demand and composition. They hypothesized that "…skill demand can, to an extent, be discovered and predicted, by tracking the skills network evolution over a series of observances derived from web-posted job adverts (p. 2)." The authors assigned weights to the connections between clusters in the evaluation of relationships.

Espejo, et al. (2021) noted that the evolution and behavior of networks could be understood by analyzing the topology of complex networks. The authors proposed using the GHuST framework to decompose muti-node networks of various sizes (e.g., Facebook, retweets, the Web, etc.) into 2- and 3-node graphlets for more manageable analysis and comparison.

Dadzie, et. al (2017) recognized the limitations of the human mind in meaningfully identifying trends in big data sets. The authors utilized task- and context-driven scenarios along with interactive graphic visualization techniques to iteratively explore and discover job skill demand trends and co-occurrences provided by job adverts found on online job boards. The graphics allowed users to visually identify the skills in most predominant demand.

Job Skill Analysis
In their work on examining job advert skill clusters, Sibarai and Scerri (2020b) described a Skills Cluster Observation and Discovery (SCODIS) framework they used to develop a forecasting model for evolving skill networks to predict future high-demand and emerging skillsets. Sun, et. al, (2021) developed a Salary-Skill Composition Network (SSCN), to extract job skills and measure their value based on immense job postings. Sun et al. (2021) proposed a valuation model that was able to assign meaningful value to job skills in various contexts outperforming other models in predicting job salaries. The authors suggested multiple applications for their model including the valuation of skills in the marketplace, salary predictions, knowledge and talent development, and guidance for job seekers. Such models can be used to address some of the current challenges faced by educators in that, with so many new technologies being introduced in industry, how do the emerging skills impact the current computing courses with dynamic job skill demand in high-tech industries?

3. ADDRESSING THE CURRENT CHALLENGE

In this paper, the authors draw upon the works of Dadzie, et. al (2017), Espejo, et al. (2021), Sibarai and Scerri (2020), Sun, et al. (2021) to develop a data driven network analytics framework to compare course content with emerging skill sets sought in online job adverts. The framework can be used to:

- identify key industry workplace competencies to develop meaningful computing course content;
- provide an analytics framework for capturing future technology trends;
- support the development of interactive data driven analytics tools for discovering curricular opportunities; and
- provide insights for fostering information and communications technology (ICT) innovations in university-industry collaborative networks.

4. THE PROPOSED ANALYTICS FRAMEWORK

The proposed framework consists of one high-level conceptual model and two analytics modules for emerging technology-centric knowledge interaction evaluation. The conceptual university-industry knowledge interaction model (Fig. 1) was created to provide a complete picture of the solution and present the key elements and their interactions in an analytics framework. The emerging technology-centric job skill network analytics module (Fig. 2) was implemented for evaluating the job market demand of the emerging technology skills related to conventional skills. The online course content analytics module (Fig. 4) was implemented for evaluating the contextual information of the emerging technologies in a conventional computing course (Clear & Parrish, 2020, p. 189; Wijesinghi, 2022, p. 56). The details are presented in the following sections.

Conceptual University-Industry knowledge Interaction Model
The conceptual university-industry knowledge interaction model, as depicted in Fig. 1, presents the agents (students, educators, and employers) in a knowledge-based society and their interactions. (Each of the three agents are represented by a node in the triangles.) If the job market demand of interconnected conventional skills and emergent skills can be measured, the educator develops tailored cross-disciplinary teaching and hands-on learning content to support the adaptive learning environment and fill the identified gaps between the emerging technology skills demanded by industry and the current computing curricula. The proposed conceptual model provides a high-level picture of an agent-based skill network with university-industry interactions with emphasis on the fact that the process is iterative.

The area to the right of the dashed line represents industry influences and the changing skill set demands of employers. The area to the left of the diagonal dashed line in the model represents the interactions and transformations taking place at the University level between Educators as Stimulators of learning and Students as Actors in the learning process. The arrows on the diagonal dashed line represent the interactions and influences that occur between industry and education (faculty and students) through the process of knowledge sharing, development, and growth. The small noded triangle sets on each

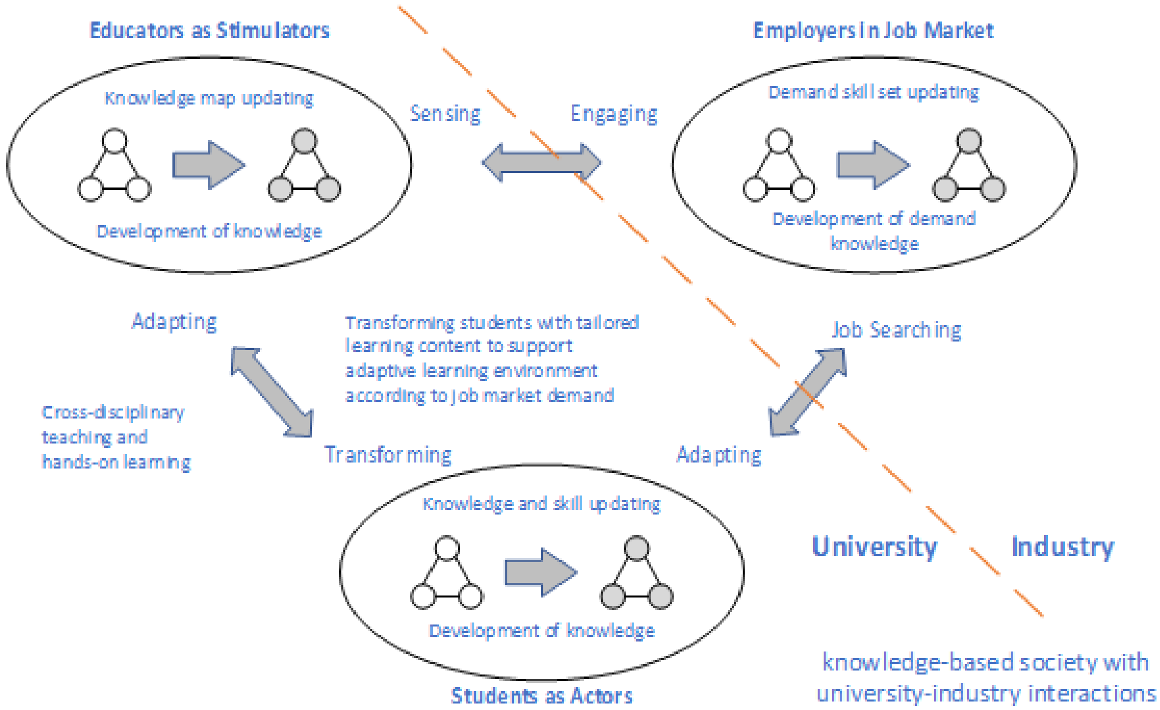

Figure 1: The conceptual university-industry knowledge interaction model.

side of the diagonal line represent the iterative process of changing states for each of the participants in the interaction process. For instance, as the faculty realize the demand for particular skills in industry, they modify the content of and their approach to teaching courses. As students learn the material, the skill set background enlarges preparing them for further development. As graduates enter the industrial workforce prepared to address new and emerging technologies, industrial actors' demand for more technical skills is further heightened. Influences in the interrelationships in the iterative process may be driven by any of the actors (e.g., Educators as Stimulators, Students as Actors, Employers in the Job Market) in each of the cycles. Thus, the model recognizes the iterative nature of the symbiotic relationships between the actors.

Emerging Job Skill Network Analytics Module

This section includes an extensive overview of the emerging job skill network analytics module with online-posted job adverts. (Fig. 2) More specifically, the authors focus on industry-demanded conventional skills having emerging characteristics. The online job advert dataset is represented as an undirected and weighted graph with a topology of interconnected skills and weight indices representing the associated strength between skills based on their observed job advert co-occurrences. The skill networks are then decomposed into six 2- and 3-node graphlets representing sets of highly interconnected conventional skills and emerging skills (Fig. 3). Through analyzing the skill graphlets, a quantitative result for evaluating job market demand for the emerging skills associated with a specific conventional skill can be provided. The role-based skill association strength is also calculated for the essential skill in leading and supporting roles based on the skill graphlets.
The proposed framework, as depicted in Fig. 2, comprises the following steps:

Step 1: Job advert dataset generation

A python program was developed to build a

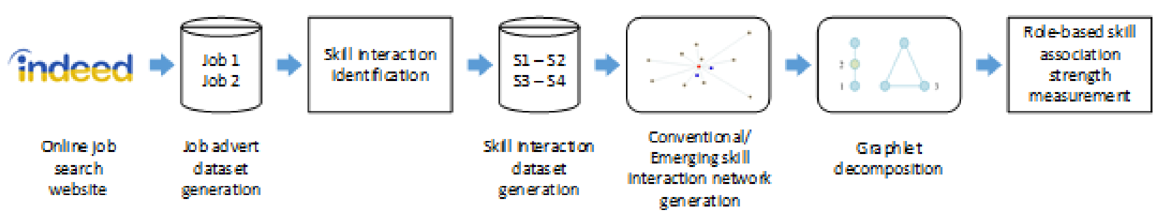

Figure 2: Emerging Job Skill Network Analytics Module Architecture

 ISSN 2167-1528
v15 n5739

pipeline for job advert dataset generation (Dadzie, et al., 2021).

Step 2: Skill interaction identification
Given a job advert with a job title string and a job context string, the skill interactions can be identified if the conventional skills and emerging skills appear in the title string and/or the context string. If the conventional skill set (*C*) appears in the title string and the emerging skill set (*M*) appears in the context string, every conventional skill is connected to every emerging skill (a complete bipartite graph) and the job advert has $C \times M$ skill interactions.

If the conventional and emerging skills only appear in the context string, the conventional/emerging skills are fully interconnected (a complete graph) and the job advert has $(C + M)$ $(C + M - 1)$ / 2 skill interactions. The emerging skills in the title string are ignored for simplification purposes.

Step 3: Skill interaction dataset generation
Given a set of job adverts, a skill interaction dataset with a set of skill interaction instances (advert ID, skill ID, skill ID) can be generated by using the skill interaction identification method.

Step 4: Conventional /emerging skill interaction network generation
Given a skill interaction dataset with the skill interaction instances, an undirected graph can be generated $G = (N, E)$, formed by the conventional skills and emerging skills $N = \{n_1, n_2, \ldots, n_N\}$ as vertices and a set $E = \{e_1, e_2, \ldots, e_E\}$ of edges $e_k = \{n_i, n_j\}$ when an advert contains the conventional skill *i* and emerging skill *j*. The weight of the edge W_{ij} is the number of job adverts in which the skill pair appears.

Step 5: Graphlet Decomposition
The generated skill interaction network can be decomposed in 2-node and 3-node graphlets (G0, G1 and G2), as shown in Fig. 3. Moreover, the G0 graphlets were labeled as $G0_L$ or $G0_S$ depending on if the advert title contained a conventional skill. In the 3-node graphlet G1, the advert title contained a conventional skill, and the advert context contained an emerging skill pair. In the 3-node graphlet G2, the advert title did not contain a conventional skill, and the advert context contained the emerging skill and an emerging skill pair (Espejo, et al., 2020; Hocevar & Demsar, 2016).

The role-based skill association strength is measured for the conventional skill in leading and supporting roles based on the skill graphlets. Similar with the SCODIS scheme (Sibarani & Scerri, 2020), the co-occurrence frequency (Callon et al., 1991) was used to calculate the skill association strength in job adverts, JA_{ij}, $JA_{ij} = (JC_{ij})^2 / (JC_i \times JC_j)$, where JC_{ij} was the number of job adverts containing the skill pair *i* and *j*; JC_i was the number of job adverts containing the skill *i*; JC_j was the number of job adverts containing the skill *j*.

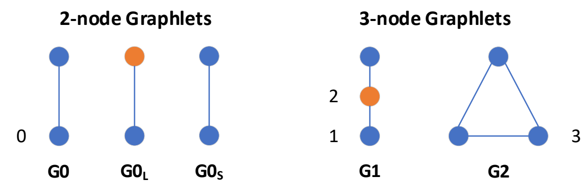

Figure 1: Graphlet Decomposition in 2-Node And 3-Node Graphlets (G0, G1 And G2). The 2-Node Graphlet G0 is also Labeled As $G0_L$ Or $G0_S$ Depending on if the Advert Title Contains a Conventional Skill. The Conventional Skill Which Appears in The Advert Title is Highlighted as Orange.

Step 6: Role-based skill association strength measurement
The leading association strength LA_{ij} can be calculated based on $G0_L$ and G1 graphlets in which the conventional skill appears in the advert title, $LAij = (LC_{ij})^2 / (LC_i \times LC_j)$, $0 \le LA_{ij} \le 1$, where LC_{ij} is the number of $G0_L$ and G1 graphlets containing the skill pair *i* and *j*, LC_i is the number of $G0_L$ and G1 graphlets containing the skill *i*; LC_j is the number of $G0_L$ and G1 graphlets containing the skill *j*.

The supporting association strength SA_{ij} can be calculated based on extracted $G0_S$ and G2 graphlets in which the conventional skill only

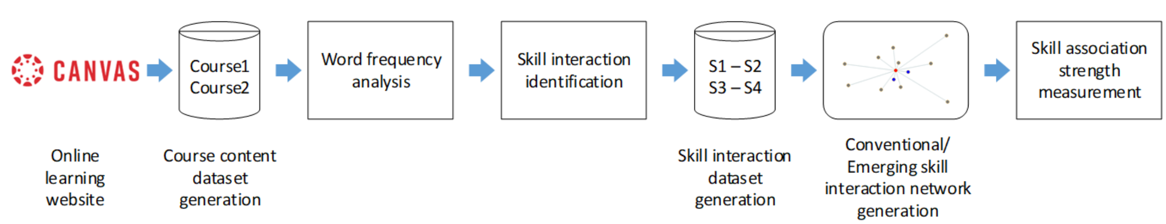

Figure 4: Online Course Content Analytics Module Architecture

appears in the advert context, $SAij = (SC_{ij})^2 / (SC_i \times SC_j), 0 \le SA_{ij} \le 1$, where SC_{ij} is the number of $G0_S$ and G2 graphlets containing the skill pair *i* and *j*, SC_i is the number of $G0_S$ and G2 graphlets containing the skill *i*; SC_j is the number of $G0_S$ and G1 graphlets containing the skill *j*.

Online Course Content Analytics Module

In the online course content analytics module (Fig. 4), a python program was developed to build a pipeline for online course content dataset generation. The online course content was extracted from the Canvas Modules learning management system pages. Through using the word frequency analysis on the online course content, the skill interactions between the conventional skill (extracted from the course title) and the emerging skills (extracted from the content) were identified. The identified conventional skill and emerging skill interactions were used to generate the skill interaction network. The skill association strength in course content CA_{ij} was then measured based on the generated skill interaction network, $CA_{ij} = (CC_{ij})^2 / (CC_i \times CC_j)$, where CC_{ij} was the number of skill interactions *i* and *j*; CC_i was the number of skill interactions containing the skill *i*; and CC_i was the number of job adverts containing the skill *j*. (Tamašauskaitė & Groth, 2022; Yu, et al., 2015).

5. A CASE STUDENT IN AN ONLINE MOBILE APPLICATION DEVELOPMENT COURSE

The influence that mobile terminal devices have had on society and the economy has been, and will continue to be, transformative. Thus, mobile app development education plays a critical role in computing related curriculums (Aimicheva et al., 2020; Babb & Abdullat, 2012). Online mobile application development courses focus on the features and capabilities of the popular mobile platforms to develop a mobile application (Leidig et al., 2020). As industry continues to integrate emerging technologies such as cloud computing and machine learning into the mobile application development process, it is critical to have a better understanding of the dynamic skill demand in the industry and adaptively adjust course content to address the required skill set (Liu & Murphy, 2012).

In this case study, the proposed data-driven emerging skill network analytics framework was used to evaluate the market-oriented knowledge interaction in an online mobile application development course. The skill network analysis and visualizations were implemented to yield more insights for bridging the “Skill Gap” in program graduates.

In this pilot research project, the authors focused on the most in-demand skills associated with mobile development skill requirements. A set of queries with the keywords “developer mobile $emerging skill” were implemented on the Indeed.com website. The query results are shown as Table 1 in the Appendix. Through use of the network analysis and visualization tools *Pajek* (Batagel & Mrvar, 2022) and *VOSviewer* (van Eck & Waltman, 2022), a conventional/emerging skill network was generated based on the Indeed query results (Fig. 5). According to the co-occurrence of the conventional mobile development skill and various emerging skills in the job adverts (Fig. 6), the most in-demand emerging skills, cloud computing and machine learning, were selected as query keywords for data collection.

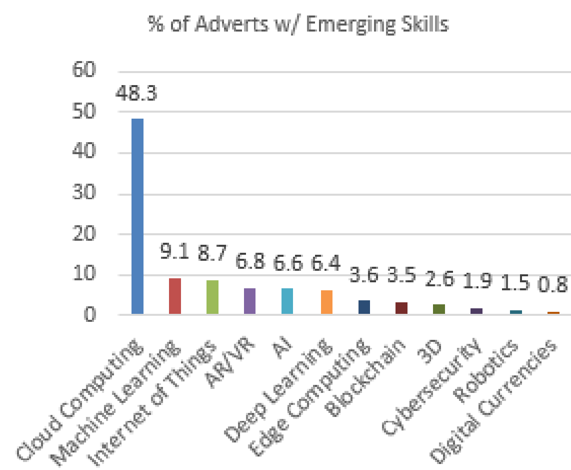

Figure 2: Percentage of Adverts with Various Emerging Skills in 33,067 Adverts Requesting Mobile Development Skills

Data collection

Job adverts derived from online job search/recruitment websites, such as Indeed, Monster, Glassdoor, FlexJobs, Ladders, AngelList, LinkedIn, Getwork, Scouted, Snagajob, etc. have been a useful mining resource for identifying demand skills in the job market (Greenacre & Hastie, 2010; Wowczko, 2015; Zhang et al., 2017; Zhao et at., 2015). A python program with the emerging job skill network analytics module was implemented to collect online job advert data from the Indeed website. In this research, a set of html files containing 3,000 online job adverts were collected consisting of 1,000 adverts from the query “developer mobile cloud”, 1,000 adverts from the query “developer mobile machine learning”, and 1,000 adverts from the query “developer mobile cloud machine learning”.

Figure 6: Indeed Query Results conventional/Emerging Skill Network

The job advert skill interaction datasets, including the mobile-cloud dataset (MC dataset), mobile-machine learning dataset (ML dataset), mobile-cloud-machine learning dataset (MCL dataset), and AD dataset with all adverts, were then generated based on the collected html files.

Another python program containing the online course content analytics module was implemented to collect online course content data from the Canvas course website at the authors' institution. In this work, the html file of the Canvas Modules page listing the course content was collected for the online mobile application development course. The online learning content consisted of 20 learning modules, 22 hands-on projects, 10 individual/group assignments, 14 Zoom class sessions, and related learning materials/resources. The course content skill interaction datasets were created based on the Canvas html file.

Modeling

Four skill networks with 13 skills as nodes and 78 weighted skill interactions as edges were built by using the job advert skill interaction datasets (MC, ML, MCL, and AD datasets) as depicted in Fig. 7. The four skill networks have the same nodes and edges with different weights on the edges. However, the authors focused only on the skill interactions between the mobile development skills and associated most in-demand emerging skills (including cloud computing and machine learning). The number of skill interactions between the mobile development and cloud computing (M-C), mobile development and machine learning (M-L), and cloud computing and machine learning (C-L) various datasets is shown in Table 2.

	MC Dataset	ML Dataset	MCL Dataset	AD Dataset
M-C	392	20	274	686
M-L	2	434	278	714
C-L	0	32	123	155

Table 2: The Number of the Skill Interactions Between the Mobile Development and Cloud Computing (M-C), Mobile Development and Machine Learning (M-L), and Cloud Computing and Machine Learning (C-L) In the MC, ML, MCL, and AD Datasets.

ISSN 2167-1528
v15 n5739

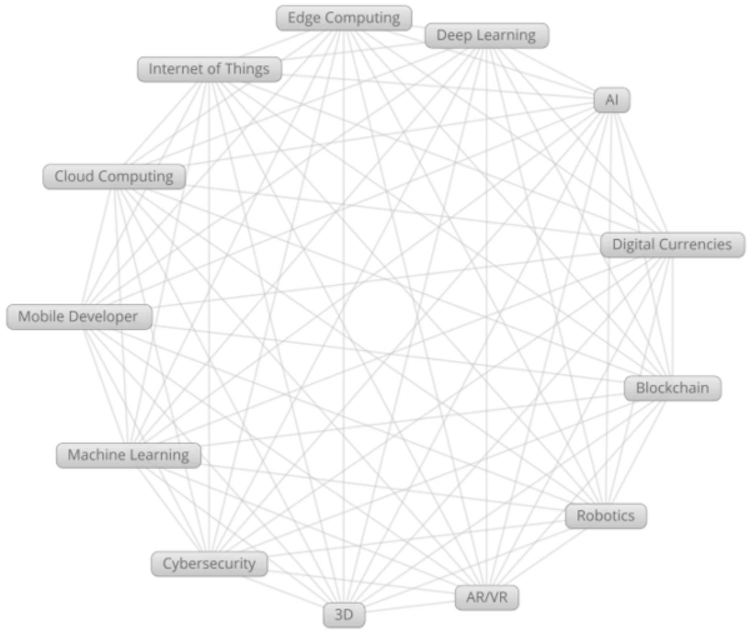

Figure 7: One of the Four Skill Networks with 13 Skills as Nodes and 78 Skill Interactions as Edges Built Using the Job Advert Skill Interaction Datasets (MC, ML, MCL, And AD). The Four Skill Networks Have the Same Nodes and Edges with Different Weights on the Edges.

The 2-node and 3-node graphlets (G0, G1 and G2) which consist only of the mobile development, cloud computing, and machine learning skills, were then extracted from the generated skill networks, as shown in Table 3.

Graphlet	MC Dataset	ML Dataset	MCL Dataset	AD Dataset
G0	394	454	552	1400
G1	0	0	0	0
G2	0	32	123	155

Table 3: The Number of the 2-Node and 3-Node Graphlets (G0, G1 and G2) Consisting Only of the Mobile Development, Cloud Computing, and Machine Learning Skills from Various Skill Networks.

A skill network with 9 skills as nodes and 8 weighted skill interactions as edges was created by using the online course content analytics module, as shown in Fig. 8. The weighted edges are represented as the top 8 high-frequency skills and the conventional skill "Mobile Development" in the Canvas Course Modules html file of the online mobile application development course (Fig. 9).

6. ANALYSIS OF NETWORKS

A set of analyses were developed based on four generated skill networks derived from various online advert datasets including MC, ML, MCL, and an Integrated AD dataset. As shown in Fig. 10, the cloud computing-related mobile developer job adverts in the MC dataset had:

- higher demand of individual cloud computing skills (39% adverts),
- very low demand of individual machine learning skills (0.2% adverts), and
- no demand of cloud computing-machine learning combining skills (no adverts).

The machine learning-related mobile developer job adverts in the ML dataset had:

- higher demand of individual machine learning skill (43.4% adverts),
- very low demand of individual cloud computing skill (2% adverts), and
- very low demand of cloud computing-machine learning combining skills (3.2% adverts).

The cloud computing- and machine learning-related mobile developer job adverts in the MCL dataset had:

- moderate demand of individual cloud computing skill (27.4% adverts),
- moderate demand of individual machine learning skill (27.8% adverts), and
- moderate demand of cloud computing-

machine learning combining skills (12.3% adverts).

requests the combined skills of cloud computing and machine learning for mobile-related developers.

Figure 8: A Skill Network with 9 Skills as Nodes and 8 Weighted Skill Interactions as Edges

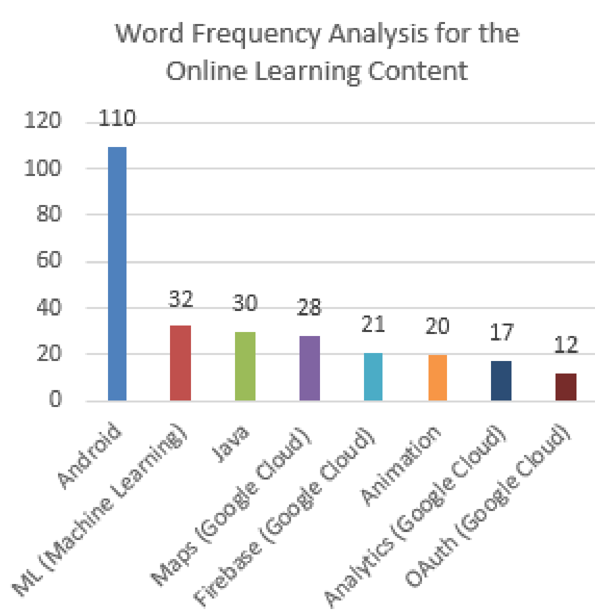

Figure 3: Top 8 High-Frequency Words Extracted from the Online Mobile Application Development Canvas Course (Total 41,520 Words of which 386 Were Unique)

According to the generated skill networks derived from online job adverts, the job market also

A set of 2- and 3-node graphlets were generated from four skill networks (MC, ML, MCL, and AD). As depicted in Fig. 11:

- cloud computing-related mobile developer job adverts had a higher demand for individual cloud computing skills (having 2-node graphlet in 39.4% adverts);
- machine learning-related mobile developer job adverts had a higher demand for individual machine learning skills (having 2-node graphlet in 45.4%); and
- cloud computing- and machine learning-related mobile developer job adverts had a
  - higher demand of individual cloud computing or machine learning skills (having 2-node graphlet in 55.2% adverts), and
  - moderate demand of cloud computing-machine learning combined skills (having 3-node graphlet in 12.3% adverts).

Through identifying the skill interactions between the job title and context in the job adverts, the roles of the skills were recognized in the generated skill networks. The following results were brought to light through the analysis:

- If the job title contained "mobile" as a keyword, the job advert was a mobile development-centric job advert. The mobile development skill was a leading skill in this job advert, the cloud computing and/or machine learning skills in the context were supporting skills.

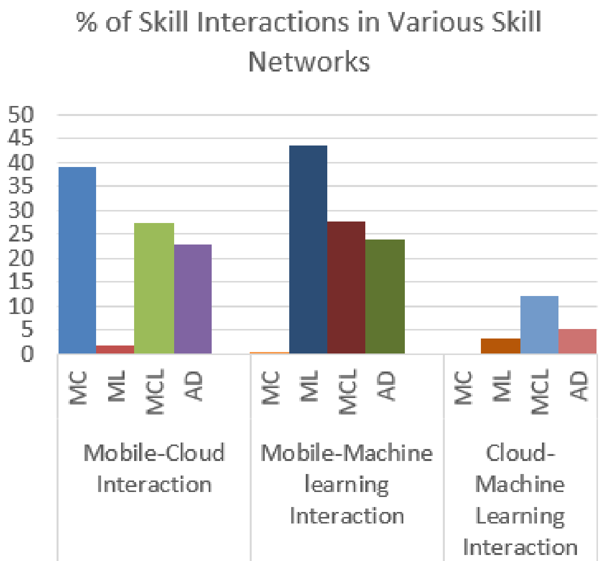

Figure 4: Percentage of Different Skill Interactions in Various Skill Networks (MC, ML, MCL And AD).

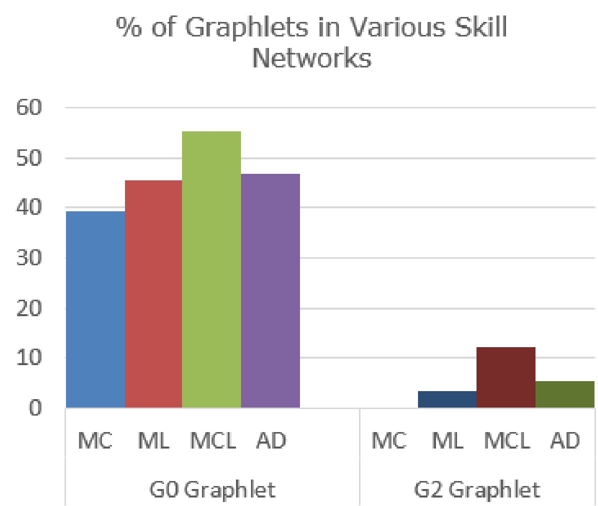

Figure 5: Percentage of 2-Node Graphlet (G0) and 3-Node Graphlet (G2) in Various Skill Networks (MC, ML, MCL, and AD).

- If the job context contained "mobile" as a keyword instead of the job title, the job advert was a mobile development-related job advert. The mobile development skill was also a supporting skill in this job advert.
- As shown in Fig. 12, the most collected job adverts were mobile development-related with the conventional mobile development skill as a supporting skill (86.8% in total adverts). Moderate cloud-related developer job adverts required mobile development skills as a leading skill (27.1% in the MC skill network).
- Most machine learning-related developers adverts required mobile development skills as a supporting skill (93.2% in the ML skill network and 94.2% in the MCL skill network).
- As depicted in Fig. 12 and Fig. 13, the mobile development-related job adverts had a higher demand for the combination of individual machine learning skills and cloud computing-machine learning skills.

The next section describes the application of the network to the skill content taught in a mobile development course at the authors' institution.

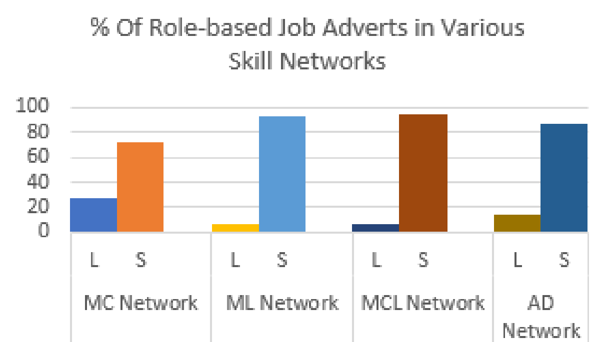

Figure 6: Percentage of Mobile Development-Centric Job Adverts (L) and Mobile Development-Related Job Adverts (S) in Various Skill Networks (MC, ML, MCL, and AD).

7. APPLICATION OF THE NETWORK TO A MOBILE DEVELOPMENT COURSE

The skill network generated from the course online content consisted of eight high-frequency words associated with the conventional mobile application development skills. Five of the words were derived from the services provided by the Google Cloud Platform (GCP) including Google *Maps*, Google *Firebase*, Google *Analytics*, and Google *OAuth*. The interaction strength between the mobile application development skill and the cloud computing skill was calculated as a sum of the frequency of the five words (Maps, Firebase, Analytics, and OAuth). The course content skill network was then generated consisting of 6 nodes and 5 weighted edges. The skill interaction strength is shown in Fig. 14.

The skill association strength was measured through multiple skill networks including the:

- course content skill network,

- AD skill network containing all collected job adverts,
- leading skill network with all mobile-centric adverts, and
- supporting skills network with all mobile-related adverts.

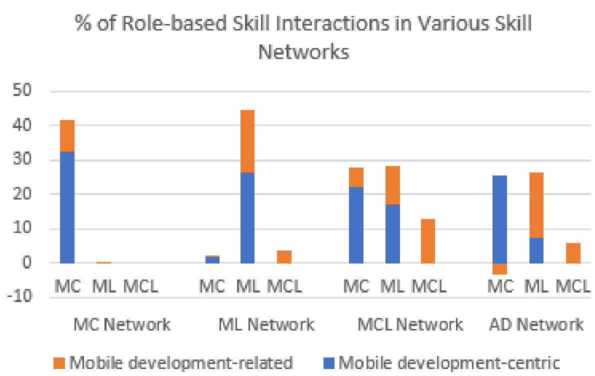

Figure 7: Percentage of Role-Based Skill Interactions in Various Skill Networks.

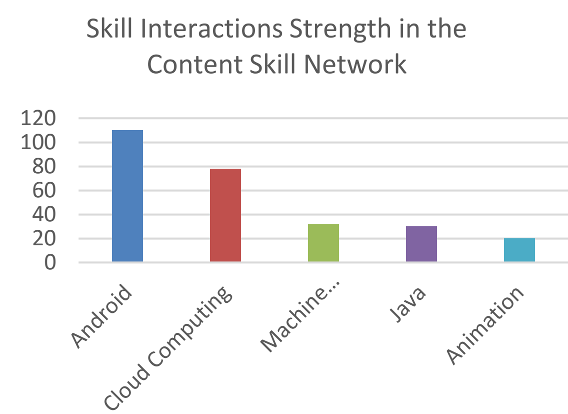

Figure 8: Skill Interactions Strength in the Course Content Skill Network with 6 Nodes (Including Mobile Development, Cloud Computing, Machine Learning, Java, and Animation) and 5 Weighted Edges.

As shown in Fig. 15, the skill association strength of the conventional mobile application development skills and the emerging cloud computing skills (0.29 in MC interactions) were higher than the strength of the mobile application development skills and the emerging machine learning skills (0.12 in ML interactions) in the course content skills network. In the next sections, the authors describe the changes that were made to the course based upon the results of the analysis.

8. Outcomes

Based on the market-oriented skill network analysis and the course content-based skill network analysis, more cloud computing- and machine learning-related learning content should be integrated into the author's current online mobile application development course. In Spring 2022, the online mobile development course was redesigned and enhanced with more emerging skill-related learning content. As shown in Table 4 in the Appendix, in addition to the original 10 mobile development hands-on projects from the previous semester, an additional 8 hands-on mobile development projects with emerging skills were incorporated including cloud computing (4), machine learning (2), cybersecurity (1), and IoT (1). Another 2 hands-on mobile development projects with data analytics skills and animation skills were also integrated. The comprehensive learning content of the new additional hands-on projects was provided on the Canvas course website including lecture notes, recorded lecture videos, study guides, project manuals, recorded project instruction videos, supplemental materials, external resource links, and forums.

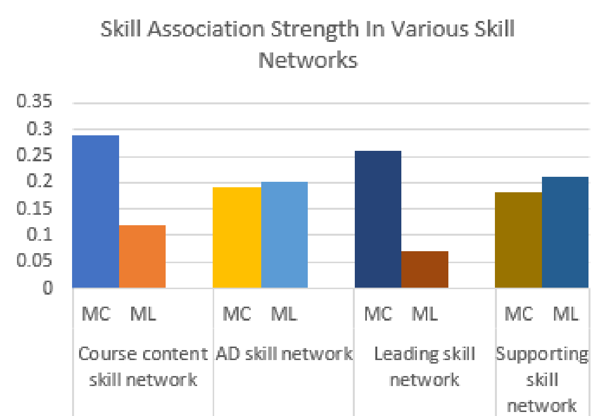

Figure 9: Skill Association Strength in Various Skill Networks Including: Course Content Skill Network, AD Skill Network w/ All Collected Job Adverts, Leading Skill Network w/ All Mobile-Centric Adverts, & Supporting Skill Network w/ All Mobile-Related Adverts

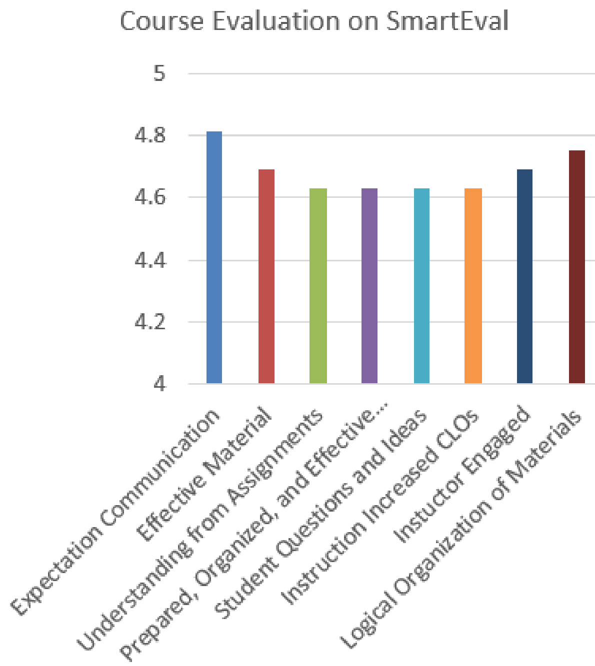

Figure 10: Average of Scores for Smarteval Course Evaluation Questions.

At the end of the semester, students evaluated the course via SmartEval. In the evaluation toolkit, eight evaluation questions were selected most reflective of the course material compilation including:

1. The expectations of the class were clearly communicated at the beginning of the course.
2. Required texts, software, or other assigned materials were used effectively in this course.
3. Exams or other major assessments accurately reflected course content.
4. The instructor gave assignments that contributed to my understanding of the subject.
5. The instructor was well-prepared, organized, and used class time and activities effectively.
6. The instructor effectively responded to the students' questions and ideas.
7. My knowledge and abilities related to this course's subject matter have increased as a result of the instruction.
8. The organization of online course materials was logical, easy to follow, and conducive to learning.

The scores were measured on a scale of five agreement levels including strongly agree, agree, neutral, disagree, and strongly disagree. 16 students participated in the evaluation with the average of the scores being 4.72/5.

The result of the average of the scores in Fig. 16 indicates that the evaluated students were pleased with the integrated course material addressing emerging technologies and felt confident about their future profession.

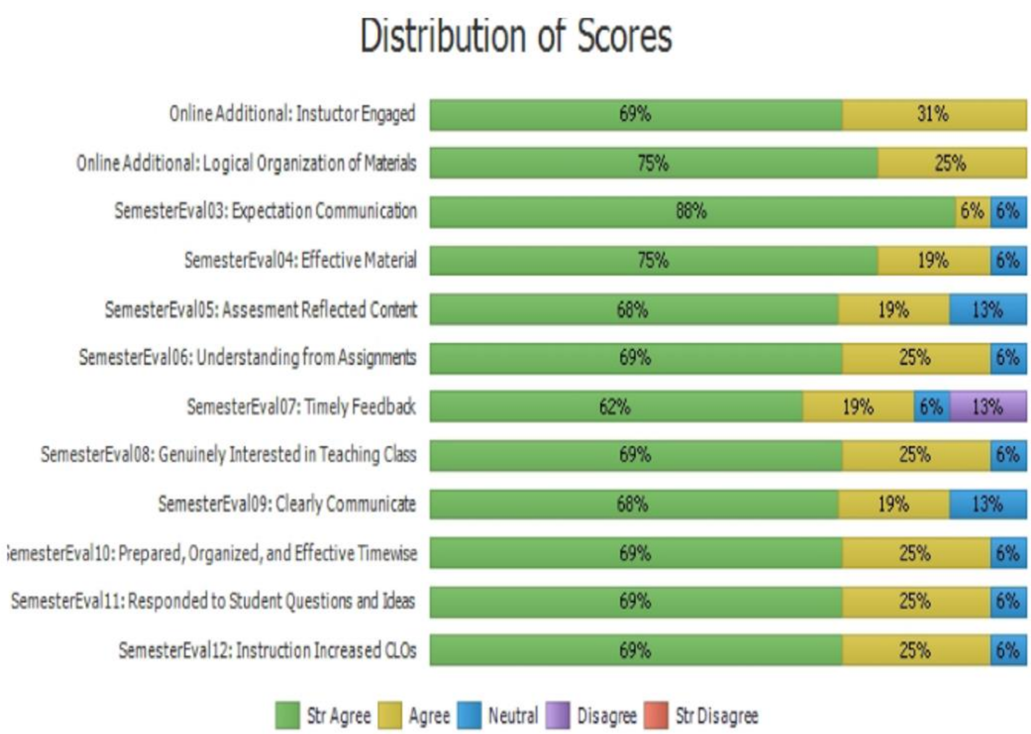

Figure 17: Distribution of Scores for Smarteval Course Evaluation Questions.

In addition, the overall course SmartEval results were encouraging since over eighty percent of the evaluated students gave positive feedback on all of the SmartEval list items, as shown in Fig. 17.

9. CONCLUSION

Ensuring that faculty teach the requisite emergent technical skills which employers need graduates to have as they enter the marketplace is imperative. In this paper, the authors described a data-driven analytics framework that can be used for evaluating emerging skill clusters in online job adverts. The framework was then applied to the content of a mobile application development course taking into account current online job advert skill set requirements. Adjustments were made to the course resulting in positive student course evaluations.

While the focus of this pilot research project was to offer and demonstrate a data-driven networked approach and technical solution to evaluating and determining course content in light of online job adverts, the effectiveness of the results is contingent upon the faculty and the demands of the employer market seeking their graduates. To effectively deliver the materials, faculty may have to adjust materials, instructional strategy, and teaching philosophy. More evaluative work needs to be done in the future regarding the impact of job market requirements in the IT industry in IS/CS program curriculum design.

In addition, in future research, the authors would like to apply the framework to further analyze other IS/IT curriculum, as well as extend the model to conduct a data-driven market-oriented skill valuation assessment across higher education modalities (conventional/online/hybrid coexistence) during the post pandemic digital transformation. The authors would also like to introduce education costs/tuition fees as a variable into the framework and compare the results with the market-oriented skill valuation framework.

10. REFERENCES

Agarwal, N., & Ahmed, F. (2017). Developing collective learning extension for rapidly evolving information system courses. *Education and Information Technologies*, 22(1), 7-37.

Arimathea, G., Zh, K., Zh, O., Tokzhigitova, N., & Akimova, S. (2020). A spiral model teaching mobile application development in terms of the continuity principle in school and university education. *Education and Information Technologies*, 25(3), 1875-1889.

Alenezi M. (2021). Deep dive into digital transformation in Higher Education Institutions. *Education Sciences, 11*(12), 770.

Babb, J. S., & Abdullat, A. (2012). The need for mobile application development in IS curricula: An innovation and disruptive technologies perspective, *Information Systems Education Journal, 10*(1), 61-74.

Batagelj, V., & Mrvar, A. (2022). Pajek: Program for Large Network Analysis (Version 5.15) [Computer Software] Ljubljana, Slovenia Available from http://mrvar.fdv.uni-lj.si/pajek/

Callon, M., Courtial, J.P., & Laville, F. (1991). Co-word analysis as a tool for describing the network of interactions between basic and technological research: The case of polymer chemistry, *Scientometrics*, *22*(1), 155-205.

Clear, A., & Parrish, A. (2020). Computing Curricula Report CC2020. Global Guidelines for Baccalaureate Degrees in Computing. New York, NY: ACM and IEEE.

Cowan, R. & Jonard, N. (2001). Knowledge creation, knowledge diffusion and network structure. In Kirman, A. Zimmermann, JB. (eds). Economics with Heterogeneous Interacting Agents. Lecture Notes in Economics and Mathematical Systems 503. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-56472-7_20

Cummings, J., & Janicki, T. N. (2020). What skills do students need? A multi-year study of IT/IS knowledge and skills in demand by employers. *Journal of Information Systems Education, 31*(3), 208-217.

Dadzie, A. S., Sibarani, E. M., Novalija, I., & Scerri, S. (2018). Structuring visual exploratory analysis of skill demand. *Journal of Web Semantics*, 49, 51-70. https://doi.org/10.1016/j.websem.2017.12.004.

de Blas, C. S., Gonzalez, D. G., & Herrero, R. C. (2021). Network analysis: An indispensable tool for curricula design. A real case-study of the degree on mathematics at the URJC in Spain, *PLoS One,* 16(3), 1-21. DOI: 10.1371/journal.pone.0248208

da Silveira Bueno, C. Masago, F. K., da Silveira,

J. M (2021). Bioenergy emerging paradigm: Collaborative networks and determinints in the upgrading process of technological frontiers. African Journal of Science Technology Innovation and Development. https://doi.org/10.1080/20421338.2021.1960540

Espejo, R., Mestre, G., Postigo, F., Lumbreras, S., Ramos, A., Huang, T., & Bompard, E. (2020). Exploiting graphlet decomposition to explain the structure of complex networks: The GHuST framework. *Scientific Reports*, *10*(1), 12884. https://doi.org/10.1038/s41598-020-69795-1

Greenacre, M., & T. Hastie. (2010). Dynamic visualization of statistical learning in the context of high-dimensional textual data. *Web semantics: Science, services and agents on the World Wide Web, 8*(2-3), 163-168. 10.1016/j.websem.2010.03.007

Hocevar, T., & Demsar, J. (2016). Computation of graphlet orbits for nodes and edges in sparse graphs. *Journal of Statistical Software*, *71*(10), 1-24. https://doi.org/10.18637/jss.v071.i10

Koong, K. S., Liu, L. C., & Liu, X. (2002). A study of the demand for information technology professionals in selected internet job portals. *Journal of Information Systems Education, 13* (1), 21-28.

Leidig, P. M., Salmela, H., Anderson, G., Babb, J., Gardner, L., Nunamaker, J. F., Scholtz, B., Shankararaman, V., Sooriamurthi, R., Thouin, M., & de Villiers, C. (2020). IS 2020: Developing an ACM/AIS information systems model curriculum for undergraduate programs. *In International Conference on Information Systems, ICIS 2020 - Making Digital Inclusive: Blending the Local and the Global)*. Association for Information Systems.

Liu, X. M., & Murphy, D. (2012). Tackling an IS educator's dilemma: A holistic model for "When" and "How" to incorporate new technology courses into the IS/IT curriculum. *SAIS 2012 Proceedings*. 31. https://aisel.aisnet.org/sais2012/31

Mitchel, A. (2022). Addressing the dynamic information technology landscape: A course reflection. *Communications of the Association for Information Systems,* 50, pp-pp. https://doi.org/10.17705/1CAIS.05020

Morris, G. J., Fustos, J. T., & Haga, W. (2018). Connecting the dots and nodes: A survey of skills requested by employers for network administrators. *Information Systems Education Journal, 16*(1), 4-12.

Sibarani, E. M., & Scerri, S. (2020). Generating an evolving skills network from job adverts for high-demand skillset discovery, In: Cheng, R., Mamoulis, N., Sun, Y., Huang, X. (eds) *Web Information Systems Engineering – WISE 2019. WISE 2020. Lecture Notes in Computer Science*, 11881. Springer, Cham. https://doi.org/10.1007/978-3-030-34223-4_28

Sibarani, E. M., & Scerri, S. (2020). SCODIS: Job advert-derived time series for high-demand skillset discovery and prediction. In: Hartmann, S., Kung, J., Kotsis, G. Tjoa, A. M., Khalil, I. (eds) *Database and Expert Systems Applications. DEXA 2020 Lecture Notes in Computer Science*, 12392. Spring, Cham. https://doi.org/10.1007/978-3-030-59051-2_25

Smith, D., & Azad, A. (2014). Analyzing computer programming job trend using web data mining. *Issues in Informing Science and Information Technology*, 11, 203-214 Retrieved June 8, 2022 from http://iisit.org/Vol11/IISITv11p203-214Smith0494.pdf

Sun, Y., Zhuang, F., Zhu, H., Zhang, Q., He, Q., & Xiong, H. (2021). Market-oriented job skill valuation with cooperative composition neural network. *Nature Communications, 12*(1), 1992. https://doi.org/10.1038/s41467-021-22215-y

Tamašauskaitė, G. & Groth, P. (2022). Defining a knowledge graph development process through a systematic review. *ACM Transactions on Software Engineering and Methodology*. *1*(1) 40 pages. https://doi.org/10.1145/3522586

van Eck, N. J., & Waltman, L. (2022). VOSviewer (Version 1.6.17) [Computer software]. Leiden, Netherlands. Available from https://www.vosviewer.com/

Wijesinghi, C. (2022). How knowledge diffusion in university-industry collaboration can foster ICT innovations in Sri Lanka, (Publication No. 978-91-7911-836-5) [Doctoral dissertation, Stockholm University] Retrieved June 9, 2022, from https://www.diva-portal.org/smash/get/diva2:1647417/FULLTEXT01.pdf

Wowczko, I. A. (2015). Skills and vacancy analysis with data mining techniques. *Informatics*, *2*(4), 31-49.

https://doi.org/10.3390/informatics2040031

Yu, X., Stahr, M., Chen, H. & Yan, R. (2021). Design and implementation of curriculum system based on knowledge graph. *IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE)*, 767-770, doi: 10.1109/ICCECE51280.2021.9342370.

Zhao, M., Javed, F., Jacob, F., & McNair, M. (2015). SKILL: A System for skill identification and normalization, In *Innovative Applications of Artificial Intelligence*, *29*(2), 4012-4017. https://doi.org/10.1609/aaai.v29i2.19064

Zhang, L., Thalhammer, A., Rettinger, A., Färber, M., Mogadala, A., & Denaux, R. (2017). The xLiMe system: Cross-lingual and cross-modal semantic annotation, search and recommendation over live-TV, news and social media streams, *Journal of Web Semantics*, *46–47,* 20-30. https://doi.org/10.1016/j.websem.2017.03.002 .

Zollman, K. J. S. (2013). Network epistemology: Communication in epistemic communities. Philosophy Compass. 8(1), 15-27.

APPENDIX A
TABLES 1 and 4

ID	Role	Conventional skill	Emerging skill	Query keyword	Co-occurrence
1	Developer	Mobile	Cloud Computing	developer mobile cloud	15,982
2	Developer	Mobile	Machine Learning	developer mobile machine learning	3,020
3	Developer	Mobile	Internet of Things	developer mobile iot	2,879
4	Developer	Mobile	AR/VR	developer mobile ar vr	2,236
5	Developer	Mobile	AI	developer mobile ai	2,186
6	Developer	Mobile	Deep Learning	developer mobile deep learning	2,112
7	Developer	Mobile	Edge Computing	developer mobile edge	1,197
8	Developer	Mobile	Blockchain	developer mobile blockchain	1,156
9	Developer	Mobile	3D	developer mobile 3d	873
10	Developer	Mobile	Cybersecurity	developer mobile cybersecurity	629
11	Developer	Mobile	Robotics	developer mobile robotics	488
12	Developer	Mobile	Digital Currencies	developer mobile currency	281
13	Developer	Mobile	N/A	developer mobile	33,067

Table 1: A Set of Queries with the Keywords "Developer Mobile $Emerging Skill" On Indeed Website.

ID	Module	Conventional skill	Emerging skill	Hands-on project
1	0	Android		Building work environment project
2	1	Java		Basic Java programming project 1
3	2	Java		Basic Java programming project 2
4	3	Android		Test run project
5	4	Android		Android Studio welcome project
6	4	Android		MPAndroidChart project
7	5	Android		TipCalculator project
8	5	Android	Cloud	Google Charts project
9	6	Android		FlagQuiz project
10	6	Android		Android View Animation project
11	7	Android		Doodlz project
12	7	Android	Cloud	Google Maps project
13	8	Android		CannonGame project
14	8	Android	Cloud	Google OAuth login project
15	9	Android		WeatherViewer project
16	9	Android	Machine Learning	Text and facial features recognition with Google ML Kit
17	10	Android		Twitter Search project
18	10	Android	Machine Learning	Text translation with Google ML Kit project
19	11	Android		AddressBook project
20	11	Android	Cloud	Google analytics with Firebase project
21	12	Android	IoT	Flutter Android application project
22	12	Android	Cybersecurity	Rooted Android Studio AVD project

Table 4: The 22 Hands-On Projects in the Online Mobile Application Development Course in Spring 2022. The New Added Hands-On Projects Were Highlighted.