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# Evaluation of Career Readiness at an Industrial Technology Program Using a Fuzzy Approach

*Keywords:*

**Career Readiness, Fuzzy Logic and  
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# Evaluation of Career Readiness at an Industrial Technology Program Using a Fuzzy Approach

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## ABSTRACT

In this research, a quantitative model to measure the “career readiness” performance level of the current curriculum of the Industrial Technology and Packaging program at California Polytechnic State University is proposed. Career readiness is first defined through performance attributes and these attributes are further classified into specific categories and metrics. Using a fuzzy logic computational approach, “career readiness” measures are developed and a “career readiness” score referred to as (CRS) is calculated. The model is designed to be flexible, dynamic and easy to use. It should enable a systematic measurement of career readiness by producing a final integrated unit-less score. Results from the data collected for the Industrial Technology program’s main employers and graduates provided various insights about the level of career readiness the program currently provides in terms of strengths and weaknesses. In addition, these results, and the developed CRS approach, may serve as a practical tool for decision-making and improvement to various educational components to increase readiness level. Finally, the overall CRS, as well as its constituting scores, can be used to monitor progress along such improvements programs.



**Ms. Kathryn Butler** earned her undergraduate degree in Industrial Technology and Packaging at California

Polytechnic State University, San Luis Obispo in 2016. The same year she also became a Certified Technology Manager from ATMAE. As a research assistant for the Career Readiness using Fuzzy Logic study and as a board member of the Industrial Technology Society her senior year, she has a great affinity in ensuring students have the best resources to start and advance their future careers.



**Dr. Olsen** serves as Area Chair and Professor of Industrial and Packaging Technology in the Orfalea College of Business at Cal

Poly in San Luis Obispo, California. Dr. Olsen teaches undergraduate and master's courses in lean thinking, six sigma, and operations management. Dr. Olsen had over 20 years of industry experience in engineering and manufacturing management at Caterpillar, Litton, and Hewlett Packard before getting his PhD at The Ohio State University. Dr. Olsen is also the Director of Central Coast Lean, a self-funded research project under the Orfalea College of Business. Its mission is to better understand how to build a community of lean practice. .

## INTRODUCTION

Although career readiness is not easy to define or measure in total, at its core, it can be simply described as the level of achievement a student needs to be ready to join and succeed in the marketplace. This means that higher education curriculum should ensure that graduating students possess key knowledge and skills sufficient to effectively begin a career path. In today's market, technically-based employers value graduates with wide-ranging skills and training in the latest technologies. Thus science, technology, engineering, and math (STEM) academic programs need to ensure that students maintain adequate career readiness levels through advanced curriculum involving experienced instructors, hands-on training, and the most up-to-date equipment.

Career readiness has become an increasingly important policy goal for many state universities. In line with this trend, California Polytechnic State University as a whole as well as its ABC school of business set a goal to ensure that the graduates will gain employment quickly and efficiently in its 2020 "strategic intent" document. However, the lack of having an assessment tool that can measure the level of performance of career readiness stands as one of the challenges in achieving this goal. This paper presents the results of a research project involving a dynamic yet simple quantitative method for the assessment of the career readiness of the graduates of the Industrial Technology and Packaging program at California Polytechnic State University.

## LITERATURE REVIEW

There are numerous work related to the assessment of student's readiness for college and postsecondary education. Examples include ACT college readiness benchmarks (2011), College Board Standards for college success (2006) and American Diploma Project Benchmarks (Rolfhus et al. 2010). However, much less research has been dedicated to career readiness assessment. Examples of such work include the research carried out by Texas College and Career Readiness standards (2009) which was developed via a convergent consensus method with teams of secondary and postsecondary educators. In addition, Conley et al. (2011) studied over 900 courses at different universities to generate common standards for both general education and career oriented courses that can capture the required knowledge and skills leading to success in

career readiness. Hooker and Brand (2010) offered an expanded definition of college and career readiness drawn from a larger review of 23 programs designed to support college and career success for students from underrepresented groups.

A discipline specific examples of career readiness include the work of Yackee (2015) and Kuhlen (2015) who both argued about the role of experiential learning in getting the law school students at University of Wisconsin ready for their career. Also Taylor et al. (2015) discussed in an extended report how pharmacy students can improve their experiential education to be more career ready. Nadler et al (2015) explored the gap between career readiness and the current education for medical students in Canada.

On a more practical side, the state of California set standards in career technical education (CTE) for 15 industries to help education institutions measure their readiness to these industries ([www.cde.ca.gov/ci/ct/](http://www.cde.ca.gov/ci/ct/) 2005). Furthermore, many industrial groups have set standards that require high levels of education and preparation. A few examples include the SAE International Standards for Aerospace, Automotive, Commercial Vehicle; the National Retail Federation for Customer Service, Retail Management, Retail Business; and the National Bioscience Industry Skill Standards for Technicians.

The previous research and developed career readiness and assessments standards are valuable guidance for institutions while developing their career readiness definition and assessment method. However, the availability of a customized and easy to apply and understand tool which focus solely on undergraduate programs is missing. This research adds to the existing literature of career readiness assessment by developing a dynamic tool that can be customized to different undergraduate disciplines to measure their level of career readiness.

### RESEARCH METHODOLOGY

Our research methodology to answer the question of how to assess career readiness in our Industrial Technology and Packaging program started by determining career readiness performance attributes based on the expectations, understanding and experience of all stakeholders (faculty,

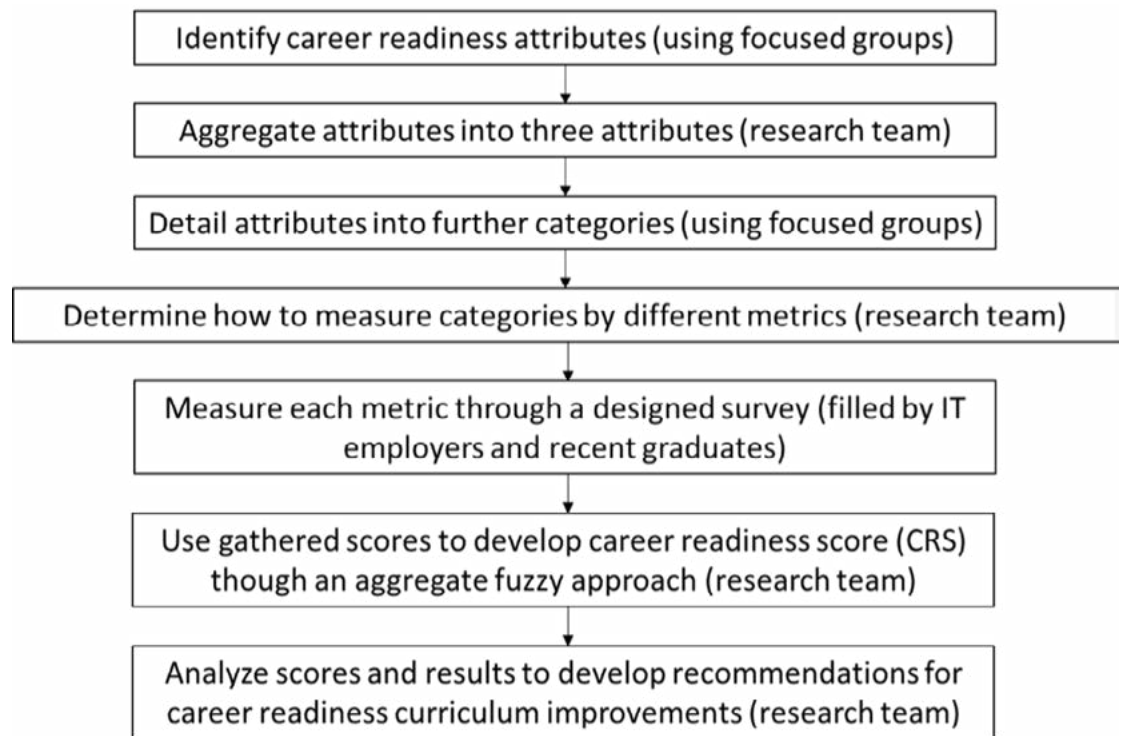
students and industrial employers). Multiple focused groups were scheduled with 23 experts and a significant effort was dedicated to compiling the list of attributes and then summarizing, aggregating and prioritizing them to select the top three attributes. The three selected attributes of career readiness and their brief definition were:

- *Knowledge*: This characteristic relates to the technical and communication skills of the employee or recent graduate.
- *Engagement*: This characteristic relates to the independence and flexibility of the employee or recent graduate.
- *Learn by Doing*: This characteristic relates to the amount of internships (experience) and campus participation the graduates took part in during their undergraduate degree.

This was followed by identifying the performance categories and metrics for each of the career readiness attributes indicated. Thus, each career readiness performance attribute was connected and further classified to the related performance categories as its surrogates. While designing a performance measurement system, it is critical to choose an efficient number of performance categories and metrics. In this research, each of the selected three attributes was measured by four or three categories and each category was further quantified by two metrics. Data was gathered from the program's graduates and employers to capture the identified metrics through well-designed questionnaires.

The next phase focused on fuzzifying the performance metric data gathered and developing the respective membership values for each category and attribute. In addition, the fuzzy membership values were calculated. Finally, the proposed career readiness score (CRS) was computed by taking the average of all membership values based on the data gathered. Figure one outlines the employed research approach and its different activities.

FIGURE 1: RESEARCH APPROACH TO DEVELOP AND CALCULATE CRS



### DATA COLLECTION AND ANALYSIS

To quantify career readiness, the research team collected input from Industrial Technology experts (professors and industry practitioners) on what skills and learned knowledge make students 'career ready'. Twelve rounds of discussions were conducted to understand the logic for each selection. This information was crucial when combining all the collected answers and putting a weighted score (level of importance) to the different attributes and their sub categories.

Once the experts' insights on what contributes to students' career readiness were gathered, the information was aggregated and grouped together. The hierarchy of attributes, categories, and metrics were analyzed to ensure all factors of career readiness were accounted for equally. Three attributes addressed the principles behind the What, How, and Why of career readiness. With careful consideration, they were labeled Learn by Doing (How: Practicing Skills), Knowledge (What: Skills), and Engagement (Why: Autonomy). Ten categories were sorted under these three attributes as shown in the Table 1.

**TABLE 1: ATTRIBUTES AND CATEGORIES FOR THE DEVELOPED CAREER READINESS SCORE (CRS)**

Attribute	Learn By Doing	Engagement	Knowledge
	Internships	Independence	Technical skills
	Campus involvement	Flexibility	Courses taken
	Level of mentorship	Ability to contribute from day 1	Oral and communication skills
			Interpersonal skills

These ten categories were further measured by metrics and the quantification of these metrics were solicited through two designed surveys based on the framework discussed by Hayes and Finnegan (2005) who used questionnaires assessed numerically on a 5-point Likert scale to evaluate each sub-measure. One survey was sent to the graduate students of the IT program and the other was slightly modified (keeping the same metrics) and was sent to the main IT graduates' employers. The structure of the survey for the CRS attributes, categories and metrics as well as a sample of the survey are shown in Appendix 1.

Before processing the data gathered from both surveys (125 from graduates and 15 from employers) into the career readiness score tool developed by the authors, a Chi-square test was conducted to check for the normality of the provided answers. The analysis revealed that at a confidence level of 95%, the answers were following a normal distribution. A sample of the test is shown in Appendix 2.

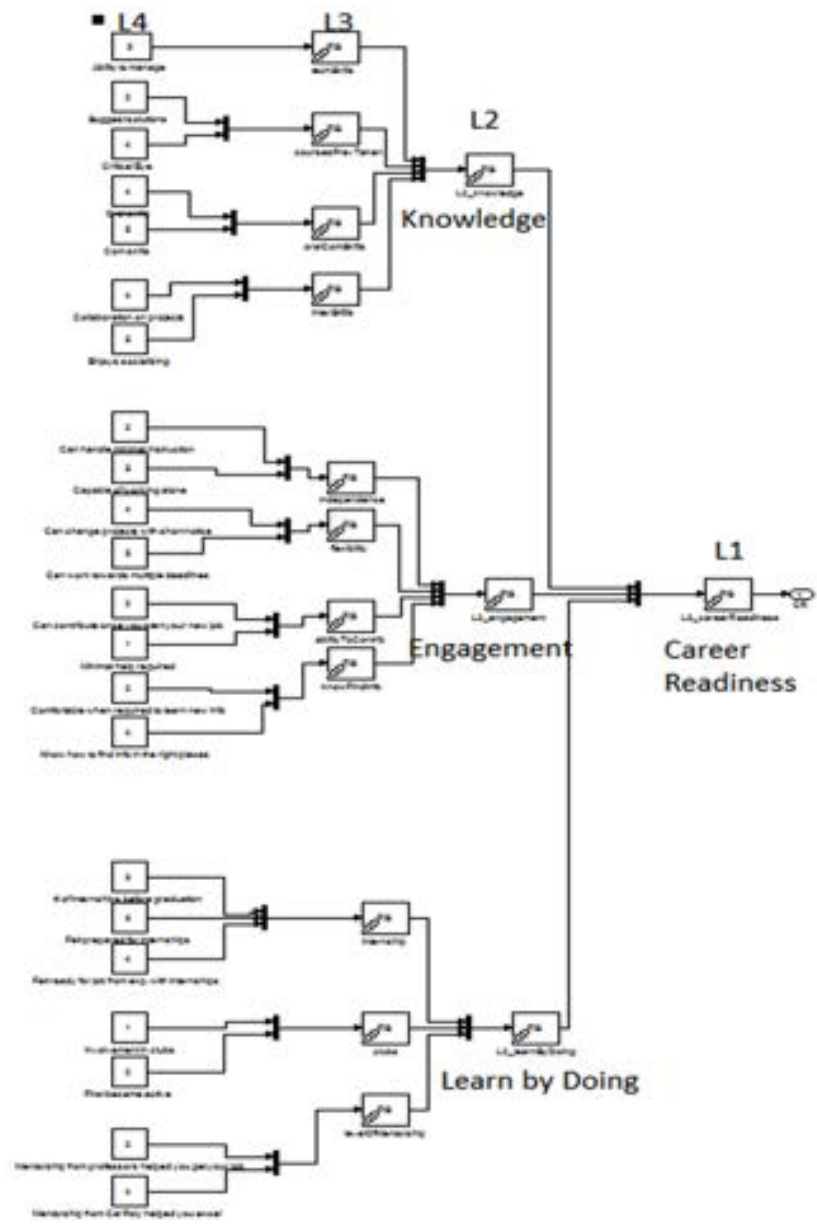
### **Career Readiness Score Tool (CRST)**

The developed career readiness score tool is based on fuzzy logic. Fuzzy logic and fuzzy sets theory were introduced by Zadeh in 1965 to provide a rich and meaningful addition to standard logic. The applications which may be generated from or adapted to fuzzy logic are wide-ranging and provide the opportunity for modeling under conditions which are imprecisely defined. Fuzzy logic joins language and human intelligence together by using the mathematics of fuzzy membership functions and provides a formal framework to represent and reason with vague, uncertain, and linguistic terms (Barnes & Hammell, 2009). This is exactly the case for the required assessment of career readiness in this research. Specifically, mapping the scores and replies from

the developed survey to the different categories and establishing logical relations between the categories and their associated attributes required functions that use linguistic variables and also mathematical operations. These functions are well developed using fuzzy logic principles described by Zimmermann (1996).

Figure 2 shows the entire structure of the career readiness score calculation tree, including the inputs, the rule blocks and the outputs. The connecting lines represent the logic flow.

**FIGURE 2: OVERVIEW OF CRST SYSTEM**

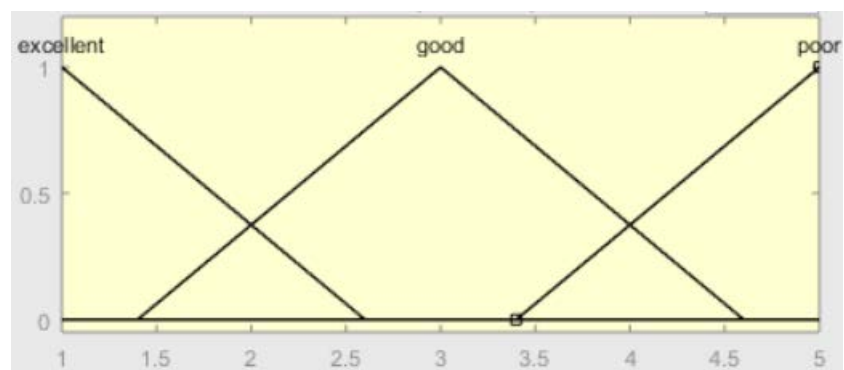




The tree shown in Figure 2 is the fuzzy approach of the methodology described in figure 1. The composition of the tree, the relevance of each input variable (metric's question) that composes the sequence of the output variable (category or attribute) and the membership functions of the fuzzy operations were revised by expert faculty in every step of the study based on previously defined career readiness measure. When calculating the overall value of a career readiness score, the process begins in the metrics level of the model (level 4). By entering a value from 1-5 for each metric's question, the rules associated with the metrics calculates and sums the score for the next level (level 3 or the categories level). From there, a summation is once again initiated and passes on the value to the next level (level 2) where the three main attributes are calculated. Once the three attributes are calculated, another summation is carried out to calculate the overall value of the career readiness score at level 1.

Three membership functions were used, represented by the linguistic terms poor (for low score of the metric), good (for average score of the metric) and excellent (for high score of the metric) for the variables in the triangular shaped function. Thus, each value obtained from the survey questionnaire was co-related to the established linguistic terms, the basis for which varied from zero to represent the poor state, to one to represent the excellent state. Figure 3 depicts the triangular membership function used. The advantages to using the triangular membership function over others, such as Gaussian and trapezoidal, are less processing power needed and overall accuracy in calculating the final career readiness score. The one downside is that more rules are needed to find an average for each individual metric and category.

**FIGURE 3: TRIANGULAR MEMBERSHIP FUNCTION USED**



Following the sequence, the rules that operate the relations among the variables are established, and the models of defuzzification are defined. The fuzzy production rules store the information in a fuzzy knowledge base. The production rules used for the composition of the thematic and systemic indicators consist of two main parts: "if" (situation) and "then" (action). While the "if" part of the rule describes the situation for which it is designed (the value of an answer from a questionnaire or a value for a certain category), the "then" part describes the action of the fuzzy system in this situation. For instance, if the three attributes, knowledge, engagement, and learn by doing are defined as poor, then the career readiness score is defined to be poor. Thus, each output variable is a result of the rule block that contains the information of all possible arrangements among input variables described in linguistic means. Examples of the rules and arrangements used are shown in Figure 4.

FIGURE 4: FUZZY RULES EDITOR

The screenshot displays the Fuzzy Rules Editor interface. At the top, a list of 9 rules is shown, each defining a condition for career readiness based on knowledge, engagement, and learnByDoing. The rules are:

1. If (knowledge is poor) and (engagement is poor) and (learnByDoing is poor) then (careerReadiness is p
2. If (knowledge is good) and (engagement is poor) and (learnByDoing is poor) then (careerReadiness is p
3. If (knowledge is excellent) and (engagement is poor) and (learnByDoing is poor) then (careerReadiness
4. If (knowledge is poor) and (engagement is good) and (learnByDoing is poor) then (careerReadiness is p
5. If (knowledge is poor) and (engagement is excellent) and (learnByDoing is poor) then (careerReadiness
6. If (knowledge is poor) and (engagement is poor) and (learnByDoing is good) then (careerReadiness is p
7. If (knowledge is poor) and (engagement is poor) and (learnByDoing is excellent) then (careerReadiness
8. If (knowledge is good) and (engagement is good) and (learnByDoing is poor) then (careerReadiness is g
9. If (knowledge is good) and (engagement is poor) and (learnByDoing is good) then (careerReadiness is g

Below the list, the interface shows a rule configuration section. It includes dropdown menus for 'If' conditions (knowledge is, engagement is, learnByDoing is) and 'Then' results (careerReadiness). Each dropdown menu has options: poor, good, excellent, none. There are also checkboxes for 'not' under each condition. The 'Connection' section has radio buttons for 'or' and 'and', with 'and' selected. A 'Weight' field is set to 1. At the bottom, there are buttons for 'Delete rule', 'Add rule', 'Change rule', and navigation arrows.

To summarize the approach, the system structure identifies the flow of the fuzzy logic analysis from the input to the output variables. The fuzzyfication in the input interface shows discreet values of the metrics in pertinence levels to the fuzzy membership functions. The fuzzy analysis takes place in blocks that contain the rules of the linguistic control (fuzzy knowledge based). The

combination of the inputs metrics into one or more outputs requires a previous definition of the relevance of each input variable in the composition of the output variable. The defuzzification is finally carried out by calculating the values for each category followed by each attribute and all are aggregated in an equal weighted sum approach to calculate the overall career readiness score (CRS) on a scale from 1-5.

## RESULTS AND DISCUSSION

Table 2 displays the summarized output from the developed CRS after fuzzyfication and defuzzification of all the inputs from the collected surveys for both the employers and the graduates.

**TABLE 2: RESULTS OF THE CRST BASED ON THE CONDUCTED SURVEYS**

	Graduates	Employers
<b>Total number of responses</b>	120	15
<b>Average value for "Knowledge" attribute</b>	2.69	2.74
<b>Average value for "Engagement" attribute</b>	2.47	2.71
<b>Average value for "Learn by Doing" attribute</b>	2.38	2.41
<b>Average value for Career Readiness Score (CRS)</b>	2.51	2.62

An analytical look at the reported results reveals different observations:

- Graduates of the Industrial Technology program on average evaluated how their program prepared them after being engaged in their careers to score around 50% of the best score (2.5 in a range from 1-5 where 1 is the best value and 5 is the worst). It is certainly debatable whether this score is at an acceptable level or not, however, it is clear that there is a room for improvement.
- On the other hand, employers of these graduates evaluated their readiness level when they joined their companies at 53%. The general small number of surveyed employers can make one a little bit cautious dealing with this score, however, it again points to the room for improvement needed by the program leaders. In addition, the close assessment between the two groups adds to the credibility of that overall value.

- In general, the assessment of the career readiness main attributes for both groups follows the pattern of ranking “Knowledge” as the highest performing attribute, followed by “Engagement” and then “Learn by doing”. The leading “Knowledge” attribute score suggests that the theoretical content of the program is not the urgent item for improvement, while the lower “learn by doing” score points to the importance of having more effort towards improving the experiential learning component.
- The detailed analysis of the answered questions for each metric can act as a template for the next improvement effort to be conducted by the program. For example, in both surveys the questions assessing campus involvement got the lowest value highlighting a priority in the improvement plan to encourage students for this kind of extra-curricular activities. Also, the knowledge attribute had the highest variation in answers from the employers indicating a challenge in the ability to assess the required and expected knowledge background needed to the IT program graduates. Finally, looking to the lowest metric in each of the three attributes of career readiness can be a good starting point for further development efforts by the program (communication skills for knowledge attribute, ability to work towards multiple deadlines for engagement attribute and campus involvement for learn by doing attribute).

### SUMMARY

Career readiness can be defined along a continuum from narrow or unidimensional to broad or multidimensional. A narrow definition is easier to measure and may be useful as a gross indicator of readiness but is less useful at the academic program assessment level. A more expansive definition is more challenging to measure, but yields more accurate data and more actionable information for program assessment. In this research, the authors strived to strike a balance between these two approaches by defining a career readiness score through few yet reflective measurable attributes and metrics for career readiness. The Career readiness score (CRS) for the Industrial Technology and Packaging program at California Polytechnic State University was defined based on three main attributes, knowledge, engagement and learn by doing, each of which was further detailed by specific categories and metrics. Assessment of these metrics were obtained from the program’s graduates and employers through numerical surveys. Using linguistic variables and linguistic rules, a fuzzy based model was developed to calculate the overall quantitative CRS.

Results of the three assessed attributes provided various insights about the level of career readiness the program currently provides in terms of strengths and weaknesses. In addition, these results and the developed CRS approach may serve as a practical tool for decision-making and improvement programs addressing different educational components to increase readiness levels. Finally, the overall CRS as well as its constituting scores can be used to monitor progress in improvements plans.

Future work will include expanding this research through gathering more data, modifying/adding more metrics and applying this approach to other programs. Finally, a sensitivity analysis can be conducted to explore the impact of having different weights for different attributes or categories (reflecting different improvement strategies and priorities) on the overall calculated CRS.

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## APPENDIX 1

The structure of the developed CRS used to develop data measurement surveys and the sent survey are shown below:

Attributes:	Categories:	Metrics:
Learn by doing	Internships:	Candidates with previous experience from internships or doing other hands-on application outside of their university were significantly more prepared for the job.
	Clubs:	Graduates with involvement in academic clubs or student leadership organizations are more prepared for the challenges in their industry since the beginning of their careers.
	Theory/Practice/Balance:	IT graduates are balanced in theory and practice.
Knowledge	Technical Skills:	IT graduates have always had a strong ability to manage/operate/control/understand existing technology.
	Courses Previously Taken:	IT graduates have always had a critical eye and ability to capture and/or define problems.  IT graduates often suggest solutions in the workplace.
	Oral and Communication Skills:	IT graduates oral communication skills were mastered when they were first hired.  IT graduates written communication skills were mastered when they were first hired.
	Interpersonal Skills:	IT graduates enjoy collaborating on projects in the workplace.  IT graduates enjoy conversing with their colleagues, business partners, and customers.
	Engagement	Independence:
	Flexibility:	IT graduates are able to change projects with short notice.  IT graduates are able to work towards multiple deadlines simultaneously.



Day 1:                    Soon after IT graduates got acquainted with their new job they were able to contribute.

The level of help/support needed for IT graduates after getting acquainted with their new job was minimal.

Finding Information:

IT graduates are ready/educated to search for new information in the right places.

### **EMPLOYERS - CAREER READINESS SURVEY**

1. Candidates with previous experience from internships or other hands-on application outside of their university were significantly more prepared for the job.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
2. Graduates with involvement in academic clubs or student leadership organizations are more prepared for the challenges in their industry since the beginning of their careers.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
3. IT graduates are balanced in theory and practice.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
4. IT graduates have always had a strong ability to manage/operate/control/understand existing technology.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
5. IT graduates have always had a critical eye and ability to capture and/or define problems.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
6. IT graduates often suggest effective solutions in the workplace.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
7. IT graduates oral communication skills were mastered when they were first hired.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
8. IT graduates written communication skills were mastered when they were first hired.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
9. IT graduates enjoy collaborating on projects in the workplace.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
10. IT graduates enjoy conversing with their colleagues, business partners, and customers.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
11. IT graduates can handle getting minimal instruction and guidance on a project.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
12. IT graduates are capable of working alone.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree

13. IT graduates are able to change projects with short notice.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
14. IT graduates are able to work towards multiple deadlines simultaneously.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
15. Soon after IT graduates got acquainted with their new job they were able to contribute.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
16. The level of help/support needed for IT graduates after getting acquainted with their new job was minimal.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree
17. IT graduates are ready/educated to search for new information in the right places.  
A. Strongly Agree B. Agree C. Neutral D. Disagree E. Strongly Disagree

### Appendix 2:

Sample of Chi-square analysis to check normality of the provided answers.

Question 16: Prob>ChiSq is <0.001 ---- Data normally distributed				
Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept[1]	0.860	0.208	17.16	<.0001*
Intercept[2]	4.700	1.004	21.90	<.0001*

Question 17: Prob>ChiSq is 0.0006 ---- Data normally distributed				
Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept[1]	0.693	0.201	11.85	0.0006*
Intercept[2]	3.054	0.458	44.53	<.0001*
Intercept[3]	4.700	1.004	21.90	<.0001*

Question 18: Prob>ChiSq is 0.0011 ---- Data normally distributed				
Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept[1]	0.653	0.200	10.65	0.0011*
Intercept[2]	3.583	0.585	37.48	<.0001*

Question 19: Prob>ChiSq is <0.001 ---- Data normally distributed				
Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept[1]	0.804	0.206	15.20	<.0001*
Intercept[2]	3.277	0.509	41.40	<.0001*