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Trends towards Predictive Mapping of Graduates' Skills to Industry Roles: A Case Study of Software Engineering

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Authors' contributions

This work was carried out in collaboration between all authors. Authors EIO and LM designed the study, wrote the protocol and supervised the work. Author FMM conducted the literature search performed the statistical analysis and wrote the first draft of the manuscript, authors EIO and LM managed the analyses and edited the manuscript. All authors read and approved the final manuscript.

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ABSTRACT

Aim: To investigate whether industry roles in the same occupation have similar academic requirements and establish learning trends in the academia towards occupational industry roles.
Design of Study: Descriptive survey research design was adopted where truism about the phenomenon under study was arrived at by gathering respondent's perception about the phenomenon.
Place and Duration of Study: This study was conducted in the Kenyan software engineering industry and universities in the academia in the month of May 2016.
Methodology: Perception from 113 employees used as respondents and 24 examinations past papers from 5 Kenyan universities both in the domain of software engineering were involved. Two

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experts, a software engineering lecturer and a pedagogy lecturer, were used to extract data from the exam past papers after their reliability test was confirmed. Both descriptive procedures and non-parametric tests of hypotheses were conducted using SPSS version 16 software and .05 as the test limit for significance. A proposed model for mapping graduate's skills to industry roles was used as the research model for the study while for academic requirements analyses purposes the model's variables were double classified into two dimensions i.e. knowledge or skill type and domain specific or domain general.

Results: Findings indicate while domain specific knowledge (χ^2=2.44, *P*=.87) and skills (χ^2=1.86, *P*=.93) for industry roles in the same occupation are similar, domain general knowledge (χ^2=13.10, *P*=.04) and skills (χ^2=16.151, *P*=.01) are significantly different for these industry roles. Further revelation indicates, while academia trends towards various industry roles within the same occupation are fairly good for knowledge (80%) and poor for skills (45.7%), trends towards various industry roles within the same occupation are not uniform among universities.

Conclusion: Academic knowledge and skills requirements for occupational industry roles are not similar and trends towards occupational industry roles are not uniform among universities. Therefore, students should select universities that have a higher trending profile for industry roles in order to increase their employability chances.

Keywords: Evaluation; mapping skills; long term unemployment; problem-solving; software engineering; trends.

1. INTRODUCTION

Global survey by ILO [1] indicates rapid growth of long term unemployment which is as a result of increased unemployment rate which currently stands at 13 per cent. Long term unemployment (LTU) is defined as continuous stay without employment for a period of at least twelve months. In Europe, the number of unemployed persons went up from 30.6 million in 2007 to 47 million in 2010, while LTU went up from 8.5 million to 14.9 million in the same period [2].

In Kenya, the number of unemployed persons increased from 1.8 million in 1998/99 to 1.9 million in 2005/2009 [3]. Empirical studies indicate that unemployment problem relates to workers willing to work but cannot find either work or meet the skill requirements of advertised jobs [3]. Findings [4] also reveal that employers have been having difficulty in finding workers with important skills, not only before but also after the economic recession of 2008 to 2010. Large companies have the highest trouble (30% before and 25% after recession), than smaller companies (19% before and 17% before recession).

Despite attempts to reduce high unemployment rates hence long term unemployment, no significant results seem to be promising. Unemployment problem seems to be elusive to measures undertaken by many affected countries including Kenya, such as increased investment, increased money supply, lowering interest rates, and enhancing labour market information systems. LTU poses serious psychological and socio-economic challenges to unemployed persons including loss of skills through human capital depreciation, loss of motivation, self-respect and dignity, and finally leading to poverty, terrorism, riots, divorce, illness and death [3].

However, LTU wouldn't be a trouble if job characteristics for each kind of workers, levels of education and skills, experience, and occupation were precisely known by new graduates; if search strategies followed by graduates improved search intensity and efficiency; if matching the characteristics employers seek against characteristics of applicants was made possible to predict probability of success long before the workers met the employer and before duration of unemployment was used as a signal of quality of the worker. Employability of skilled graduates in the industry is a challenge not only because of the effect of unemployment duration, but due to increased skills variation among both graduates and industry roles, emanating from the industry academia gap [5].

The main focus of this paper is to examine the potential of evaluating both industry roles requirements and learning trends in the academia towards industry roles using a predictive model for mapping graduates' skills to industry roles. The rest of this paper is organized as follows: the rest of this section highlights industry academia gap, the way forward to bridge the gap, reviews to related work, the problem statement, and the proposed model, section 2 discusses methodology of the study, section 3 presents data analysis results and discussion, and section 4 closes with conclusion and recommendations.

1.1 Industry Academia Gap

Employers describe staffing requirements in terms of competences while academia expresses skills and knowledge characteristics in terms of certifications and qualifications [6]. As a result, there is increased confusion among graduates in understanding employers' preferences [7,8,5].

Currently, graduates' skill variations and other factors contribute to industry academia gap [9,5]. For instance, many degree programs have similar titles but lead to graduates with different competences [10,5]. This is due to differences either in learning environments among institutions [11] or between students' abilities [12,10,5]. As a result, employers have difficulty in selecting graduates with the right skills due to skill diversity among graduates.

Besides, industry has a picture of competences that graduates should possess for each job, such as problem solving skills [13,8]. But, traditional classroom evaluation is limited to learning objectives and still uses grades to signal problem solving skills. Yet, apart from grades suffering variation from grader to grader [14], problem solving skill is multidimensional [15,16] and signals employers use to assess it such as interviews and grades, are also not sufficient [8].

Graduates seek insight into which job prospects look favorable and understand requirements in terms of skills characteristics [17]. Although requirements thresholds for problem solving skills vary differently for different jobs [18,11], precise levels and types needed by each are poorly understood [17]. A standard evaluation method that not only helps employers see through the skill qualification mix of graduates but also evaluates all dimensions of problem solving skills is needed to bridge this gap [10,5,11].

1.2 Challenges Facing Academia Evaluation Methods

1.2.1 Low graduates' productivity

Recent studies have shown that employers are not satisfied with knowledge and skills of new graduates [9,19] hence raising dissatisfaction over graduates' productivity. There is an obvious difference between the industry needs and the actual supply from academia [9], hence causing a gap between academia and industry.

1.2.2 Poorly understood skill trends

Trends indicate significant evolution of technologies that demand strong problem solving skills, and evolution of skill requirements for professionals [20,21,22,23,24]. Long term trends have been towards jobs requiring more education and cognitive skills, but the precise levels and kinds of skills are poorly understood by graduates in the academia [17].

1.3.3 Poor detection of underlying causes of industry academia gap

Studies reveal there is a gap between industry and academia, but none has been able to show one of the underlying causes is poor evaluation of problem solving skills of graduates by both industry and academia [25,26,18,27,28]. Studies on evaluation of graduates' competences indicate problem solving skill is poorly evaluated [13,8] hence causing industry academia gap.

1.3 Challenges Facing Industry Evaluation Methods

1.3.1 Lack of evaluation objectivity

Traditional competence evaluation methods such as interviews, grades, manual grading etc. are not sufficient for problem solving skills [8] and are subjective [29,11], and have no underlying framework of reference that is cognitively based [12].

1.3.2 Lack of incorporation of key elements that improve performance in the Job

There are issues in evaluation and prediction of graduates' skills such as, content knowledge evaluation is not adequate, there is need to also evaluate competences [13]; qualifications and certifications alone do not adequately portray graduates' skill possession [5].

1.3.3 Lack of reliable formula for performance prediction

There is no reliable formula to combine competences to predict overall graduate's capability [6]. Matching characteristics employers seek against characteristics of new graduates is difficult. A standard evaluation method that helps employers see through the skill qualification mix of graduates but also evaluates all dimensions of problem solving skills is needed.

1.4 Towards Bridging Industry Academia Gap

While industry academia partnership is key to bridging the gap [30], graduate evaluation against industry jobs is vital. Evaluation method that is both industry and academia centered can reduce not only confusion among graduates in understanding employers' preferences [8,5], but also difficulty of matching characteristics employers seek against characteristics of new graduates. Further, solution to these challenges may require certain key facts and strategies such as, to perform job tasks properly in the industry core content knowledge and experience are key requirements [27], content knowledge alone is difficult to apply in unfamiliar context [13]. Strategies that focus on understanding issues such as, relationship between content knowledge and competences, use of competence evaluation frameworks, and automatic skill evaluation using computational intelligence are key towards bridging the gap [14,29,31].

1.5 Related Work

Ludi & Collofello [25], analyzed and mapped undergraduate Software Engineering (SE) course content to Software Engineering Body of Knowledge (SWEBOK) content using Bloom's taxonomy [32] and was able to identify gaps in the SE content. Although most of the SWEBOK topics were covered in the SE courses there were lots of gaps in the level of knowledge expected by the SWEBOK content. Ludi & Collofello [25] findings suggest possible ways to bridge the gap and indirectly imply that knowledge and skills trends in the academia need to be matched with industry role requirements so as to reduce the gap. Surakka [23], revealed kind of technical skills software developers need and grouped them into five categories: platform skills, programming skills, networking skills, database skills and distributed technology skills. Surakka's [23] study findings not only reveal increasing trend of the number of individual technical skills in each category, but also suggest possible knowledge and skills differences between industry roles in the same occupation. Surakka's [23] study further recommends creation of job skills database and direction of research towards entry-level positions that show relevance of graduates towards employability. Also, Shkoukani [9] investigated the ability of Jordanian universities to provide well qualified SE graduates to SE industry, proposed and tested a model that revealed Jordanian universities do not have the ability to produce qualified SE graduates. Combining the findings of these three related studies there is need to document industry role requirements in a job skills database and map them to knowledge and skills in the academia. As a result, Mwakondo et al. [33] derived a conceptual model [33] that represents the most possible key factors of a worker associated with enhanced performance in the job, which were identified through analysis of learning outcomes described by common models for training and learning evaluation, such as Kirkpatrick's, CRESST's [15], and Kraiger's models [12]. The current study is an extension of all these studies: 1) create an entry-level job skill database 2) use a model to map knowledge and skills in the academia with entry-level job skills requirements to reveal academia trends towards these jobs.

1.6 Statement of the Problem

Academia does not meet the industry needs as a result of industry academia gap. While the industry is facing a problem of finding skilled graduates who fit to their needs, academia is facing a problem of matching their graduates' skills with industry roles. Somehow, the gap is a problem of training evaluation where achievement of training objectives is over-emphasized at the cost of evaluation that enhances both employability of graduates and performance in the job. While potential solution to this problem can be the use of a predictive model for mapping graduates' skills to industry roles using computational intelligence, evaluation of both industry role requirements and learning trends in academia towards industry roles is vital. This paper examines the potential of such a model in evaluating both industry roles requirements and learning trends in the academia towards industry roles. The paper seeks to answer the following two research questions that highlight the problem identified in this paper:

1) Are there significant differences in knowledge and skills requirements of various industry roles in the same occupation?

2) What are the trends in knowledge and skills in the academia towards these industry roles?

1.7 Objectives

To investigate knowledge and skills trends in the academia towards different occupational industry roles using a proposed model for mapping graduate's skills to industry roles.

1.7.1 Specific objectives

1) To establish knowledge and skills differences among industry roles in the same occupation
2) To identify knowledge and skills trends in the academia towards industry roles

1.8 Research Questions and Hypotheses

RQ1: are there significant differences in knowledge and skills among various occupational industry roles?

Two research hypotheses were defined to be investigated in order to answer this research question:

1) H_{01}:There are no significant knowledge differences between industry roles in the same occupation
2) H_{02}:There are no significant skill differences between industry roles in the same occupation

RQ2: what are the trends in knowledge and skills in the academia towards occupational industry roles?

1.9 Proposed Model

Mwakondo et al. [33] derived a research model that represents the key factors of a worker associated with enhanced performance in the job, which were identified through analysis of learning outcomes described by common models for training and learning evaluation, such as Kirkpatrick's, CRESST's [15], and Kraiger's models [12]. The study hypothesized that the problem solving competence requirement of an industry role can be determined by five cognitive factors: Content knowledge (Relevancy), technical skills (Accuracy), cognitive skills (Durability), academic capacity of individual's ability (Capacity) and Attitude-Motivational factors. Therefore, content knowledge, cognitive skills, technical skills, and academic capacity are independent factors or variables and are henceforth represented as Relevancy, Durability, Accuracy, and Capacity respectively in the proposed model. All the variables will be measured on a liker scale range of 1(least important) to 12 (most important) points .The figure below (Fig. 1) shows the proposed mapping model.

2. METHODOLOGY

A survey is a formal investigation performed in retrospect to gather data on a phenomena that has been prevailing for a while using questionnaires and/or structured interviews then analyzed using quantitative statistical techniques to reveal the findings in order to get a clear picture of the phenomena at a single point in time. Based on their purpose, there are three types of surveys: explorative, descriptive, and explanatory. Descriptive survey enables the researcher to make assertion about a population

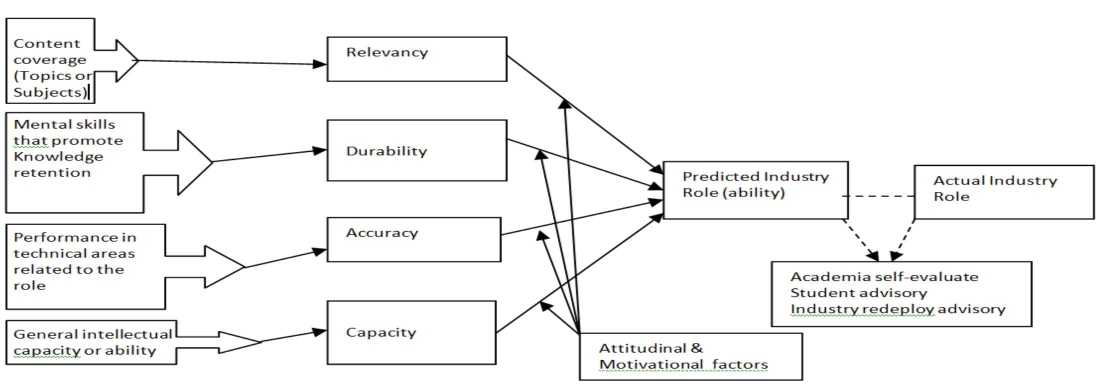


Fig. 1. The proposed mapping model as adapted from training evaluation model (Kirkpatrick, 1956), learning evaluation model [15], training evaluation model [12]

while explanatory survey enables the researcher to make explanatory claims about a population, and explorative survey enables the researcher to foresee important issues before the main study is carried out. There is sufficient evidence that surveys have been used successfully elsewhere in computing [34]. In the context of this study, employees have been holding industry roles for quite a while and the researcher believes they have sufficient insight of the academic and technical skills requirements for those positions. Therefore, descriptive survey was sufficient to make assertion about the populations under study about a phenomenon known as industry roles. The use of surveys allows a researcher to study many variables at one time as it is in this study.

The rest of this section explains the details of the methodology used in this study.

2.1 Sampling Population

In order to answer the research questions, a survey was conducted on two populations in the occupation of software engineering: past exam papers of degree programs in the academia (both private and public universities in Kenya) and graduate employees in Kenyan software industry. Three degree programs, computer science, information technology and software engineering, were identified as training grounds for software engineering in the academia. A list of all Kenyan universities offering these programs at undergraduate level was prepared and random sampling was used to select 5 universities before random sampling was applied to pick 24 exam past papers in software engineering course. This study focuses on only undergraduate degree programs because the main aim is to promote employability of fresh bachelors' degree graduates. A total of 55 software firms were used to sample 150 software developers as respondents randomly. Two types of questionnaires were used, one to analyze the exam past papers while the other for respondents. Out of 150 questionnaires sent to the respondents, 124 were returned and only 113 were valid.

A domain expert in software engineering was used to extract the data on relevant content knowledge while domain expert in pedagogy was used to extract data on cognitive skills from exam past papers. For each exam past paper, each question was split into two parts i.e. verb and topic parts. The verb part was used as the indicator for the cognitive skills, while the topic part was used as the indicator for the content knowledge. Bloom's taxonomy [32] was used as a reference framework for extracting cognitive skills from each question's verb part, while software engineering body of knowledge (SWEBOK) guide version 2014 was used as a reference framework for extracting content knowledge from the topic part of the question.

2.2 Reliability Test and Validation of Research Instrument

The two domain experts were each first used to evaluate one past exam paper twice and their results were correlated for reliability before they were adopted for the rest of the work. Test-retest method was applied and Karl Pearson's product moment correlation coefficient, r, was greater than 0.98 for both cases. The two questionnaires were subjected to an expert in questionnaire design and necessary changes were made as suggested by the expert. The respondent questionnaire was then administered to 10 respondents with several question items testing the same concept and the results were correlated for internal consistency. Again, Cronbach's alpha coefficient of reliability was good (α =.91).

2.3 Statistical Methods

Preliminary preprocessing of the data was conducted using Microsoft office Excel 2007 before the data was transferred to SPSS version 16 for the further analysis. For analyses, both graphical and descriptive analysis procedures were used, while for significance tests, non-parametric methods were used and .05 was used as the test limit for significance.

3. RESULTS AND DISCUSSION

3.1 Population Description

Tables 1a and 1b describe the demographic characteristics of exam past papers' sample and employees' sample.

3.2 Proportions of Job Entry Industry Roles

Fig. 2 presents pie chart results showing common industry roles undertaken by software engineers in the industry at job entry level after graduation and their proportions (%) as revealed by the survey. While 'web programmer' and 'analyst programmer' are very popular at job entry level 'project manager' is not.

Table 1a. Demographic characteristics of exam past papers sample

Variable	Category	Frequency	Percentage (%)
1. Degree program	BSc. Computer science	15	62.5%
	BSc. IT	9	37.5%
2. Year studied	Second year	4	16.7%
	Third year	10	47.7%
	Fourth year	5	20.8%
	Second and third year	5	20.8%
3. Number of questions	Four	5	20.8%
	Five	14	58.3%
	Eight	1	4.2%
	Ten	4	16.7%
4. Total exam marks	90	5	20.8%
	110	14	58.3%
	160	3	12.5%
	170	1	4.2%
	180	1	4.2%

Table 1b. Demographic characteristics of employees' sample

Variable	Category	Frequency	Percentage (%)
1. Gender	Male	77	68.1%
	Female	36	31.9%
2. Bachelor's degree	BSc. Computer science	32	28.3%
	BSc. IT	55	48.7%
	BSc. Software engineering	22	19.5%
	Others	4	3.5%
3. Attractor to job	Passion	31	27.4%
	Salary	33	29.2%
	Ambition	33	29.2%
	Qualification	7	6.2%
	Other	9	8.0%
4. % of classroom learnt content tested in exam	100%	4	3.5%
	75%	73	64.6%
	50%	33	29.2%
	25%	2	1.8%
	0%	1	9.0%

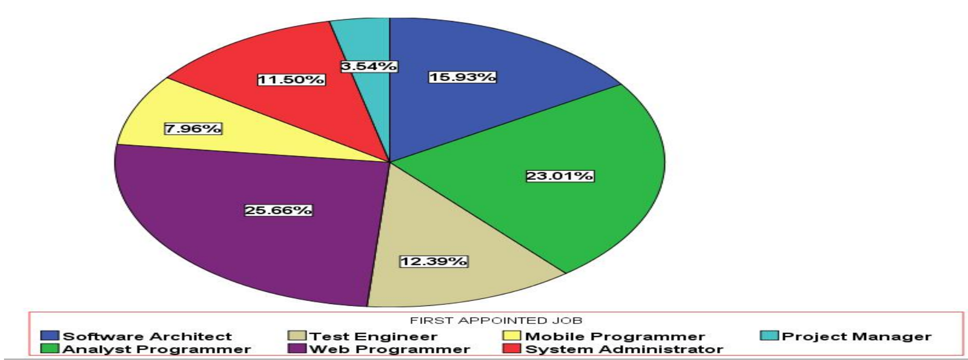


Fig. 2. Industry roles for software engineers

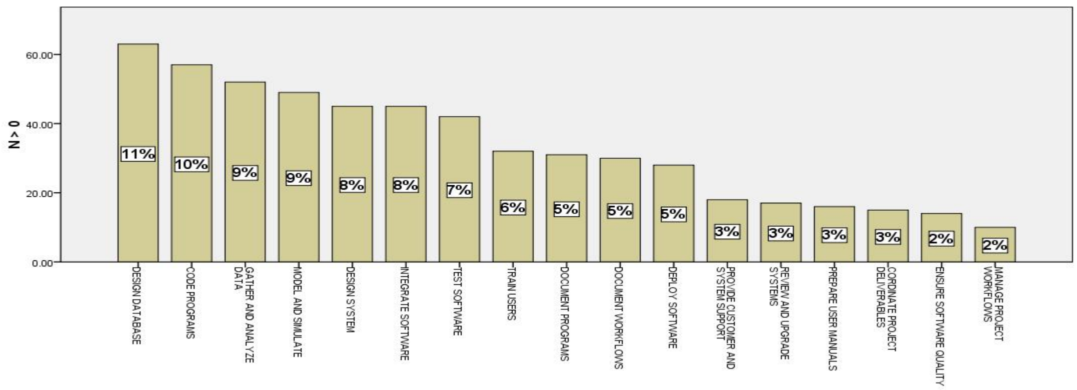


Fig. 3. Role performance activities for software engineers' industry roles

3.3 Proportions of Job Entry Level Role Performance Activities

Fig. 3 presents a bar graph showing frequency analysis results of a total of 17 role performance activities (RPA) performed by software engineers in various industry roles at job entry level as revealed by the survey. The results reveal RPA 'design data base' is the highest performed (11%) while 'manage project workflows' is the least (2%).

3.4 Central Tendency Measures

Both mean and mode were used to describe the central tendency of the independent variables. However, before further analyses were conducted, reduction of data redundancy using principle component analysis method was performed on the study's data file. A total of 24 original sub-variables for analysis were reduced to 13 components or factors, hence considerably reducing data complexity with little loss of accuracy information of only 13.71%. The 13 components represent 13 sub variables that were used to assess respondents' perception on the four factors that can be used to determine graduates suitability for various industry roles as indicated in the research model's input variables and as described below:

3.4.1 Independent variable 1 – Relevant content knowledge that promotes enhanced performance in the industry role

Out of the original 10 sub-variables only three were uncorrelated i.e. 1) software requirement 2) software configuration, and 3) software quality. Figs. 4a, 4b, and 4c present bar graph results showing comparison of average content required of various knowledge areas to perform each industry role. Mode was used as the measure of central tendency and the results reveal knowledge content type 'software requirements' and 'software quality' are least relevant to 'analyst programmer' while 'software configuration' is least relevant to 'project manager'. However, 'software requirements' and 'software configuration' are highly relevant to 'systems administrator' while 'software quality' is most relevant to 'test engineer'. Finally, the relevance index (meanR) was calculated by getting the average of the three sub-variables and the mean was used as the measure of central tendency. Fig. 4d presents bar graph results showing comparison of the means for the relevance index of the various industry roles. The results indicate 'systems administrator' has the highest relevance index (8.718) while 'web programmer' has the least relevance index (8.057).

3.4.2 Independent variable 2 – Cognitive skills that promote prolonged retention of relevant knowledge required to perform the industry role

Out of the original 6 sub-variables only three were uncorrelated i.e. 1) concept understanding 2) concept application, and 3) concept judgment. Figs. 4e, 4g, and 4f present bar graph results showing comparison of average level required of various types of cognitive skills to perform each industry role. Again, mode was used as the measure of central tendency and results indicate industry role 'analyst programmer' demands highest levels of skill type 'concept understanding' and 'concept application', while 'test engineer' and 'project manager' demand levels for these skill types are the lowest.

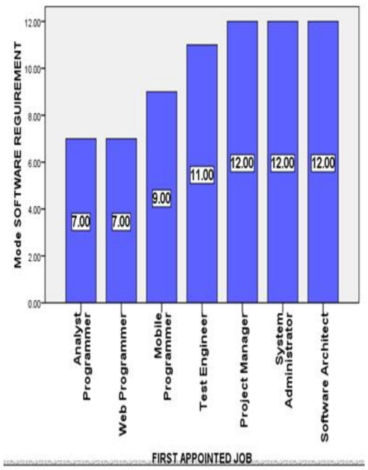


Fig. 4a. Average software requirements knowledge content required for each industry role

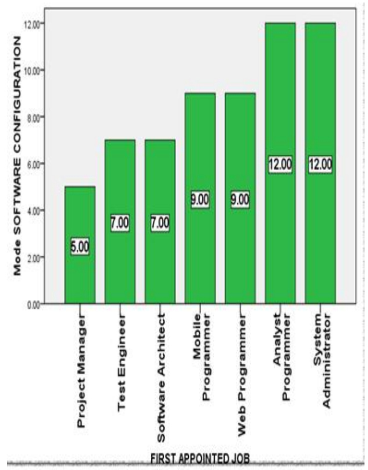


Fig. 4b. Average software configuration knowledge content required for each industry role

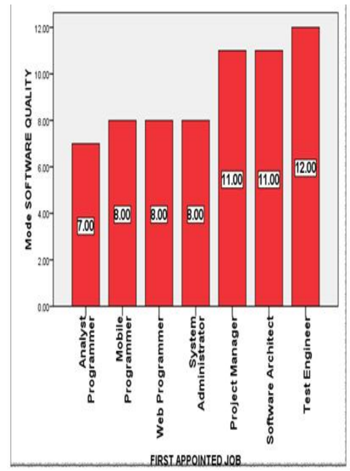


Fig. 4c. Average software quality knowledge content required for each industry role

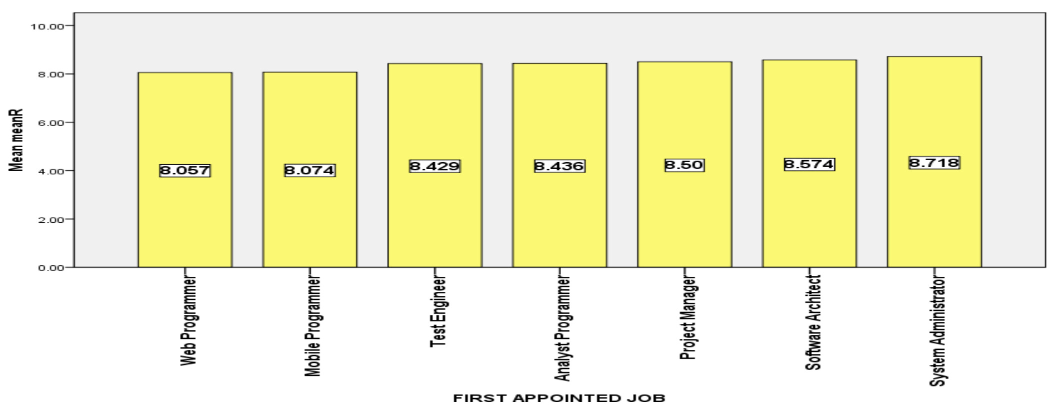
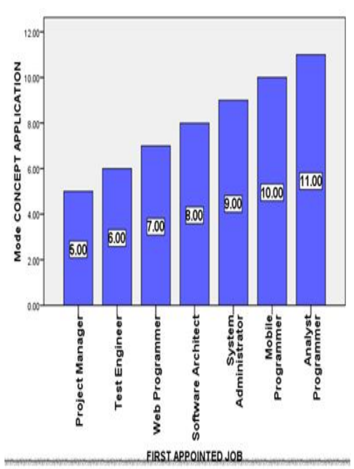
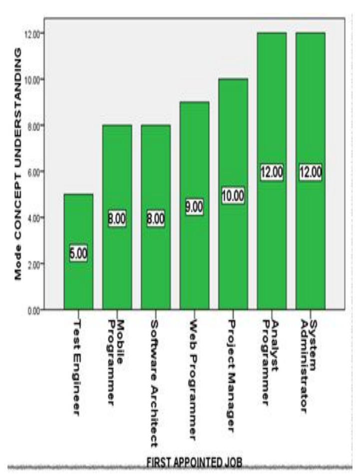


Fig. 4d. Average relevance index for each industry role





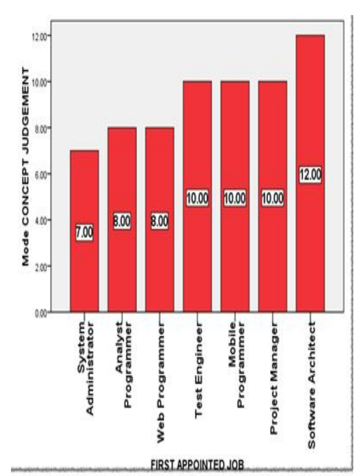


Fig. 4e. Concept application skill required for each industry role

Fig. 4f. Concept judgment skill required for each industry role

Fig. 4g. Concept understanding skill required for each industry role

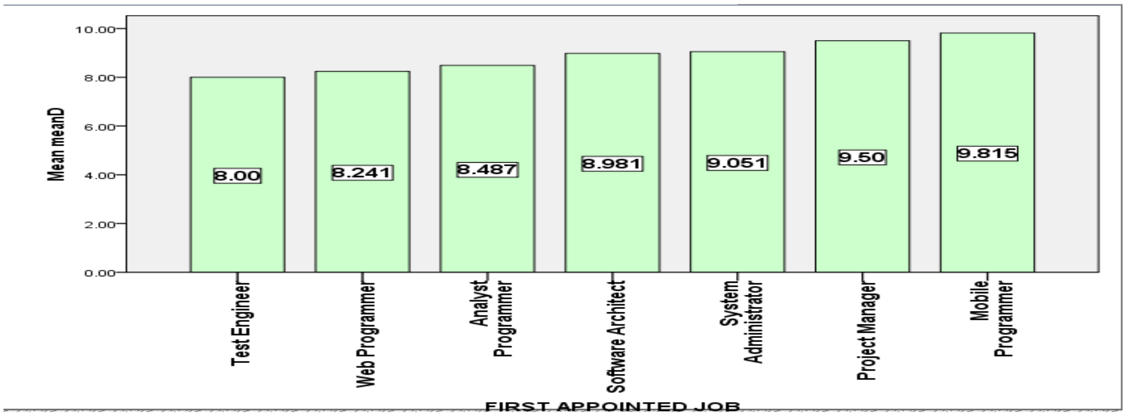


Fig. 4h. Average durability index for each industry role

However, 'concept judgment' demand levels are very high for 'software architect' and very low to 'systems administrator'. Finally, the durability index (meanD) was calculated by getting the average of the three sub-variables and the mean was used as the measure of central tendency. Fig. 4h presents bar graph results showing comparison of the means for the durability index of the various industry roles. The results indicate 'mobile programmer' have the highest durability index (9.815) while 'test engineer' have the least relevance index (8.0).

3.4.3 Independent variable 3 – Technical skills that promote precision of performance results in the industry role

Out of the original 6 sub-variables five were uncorrelated i.e. 1) SE project 2) database skills 3) programming skills 4) networking skills, and 5) distributed skills. Fig. 4i presents bar graph results showing comparison of average level required of various types of technical skills to perform each industry role. Again, mode was used as the measure of central tendency and results indicate industry roles 'analyst programmer', 'test engineer', 'web programmer', and 'mobile programmer' have similar demand levels of all skill types while the rest reveal some variations. Finally, the accuracy index (meanA) was calculated by getting the average of the five sub-variables and the mean was used as the measure of central tendency. Fig. 4k presents bar graph results showing comparison of the means for the accuracy index of the various industry roles. The results indicate 'systems administrator' has the highest accuracy index (10.342) while 'project manager' has the least relevance index (9.525).

3.4.4 Independent variable 4 – Intellectual content that promotes capacity to perform the industry role

All the two original sub-variables are uncorrelated i.e. 'O' level Aggregate points and Bachelors final grade. Fig. 4j presents bar graph results showing comparison of average level required of various types of intellectual content to perform each industry role. Again, mode was used as the measure of central tendency and results indicate only industry roles 'test engineer' and 'web programmer' have their content type values paired different while the rest reveal their pairs are tying. However, it is important to note that there are two blocks of ties, lower and upper. Industry roles 'software architect' and 'analyst programmer' have the lowest similar tie, while 'project manager ',' systems administrator and 'mobile programmer' have the highest similar tie. Finally, the capacity index (meanC) was calculated by getting the average of the paired sub-variables and the mean was used as the measure of central tendency. Fig. 4l presents bar graph results showing comparison of the means for the capacity index of the various industry roles. The results indicate 'project manager' have the highest capacity index (9.0) while 'software architect' have the least capacity index (7.083).

3.5 Hypothesis Testing

Table 2a: presents results of non-parametric test for multiple independent samples that was conducted using factor values derived during data redundancy process, to test the research hypotheses. The results were used to answer research question 1 of the study.

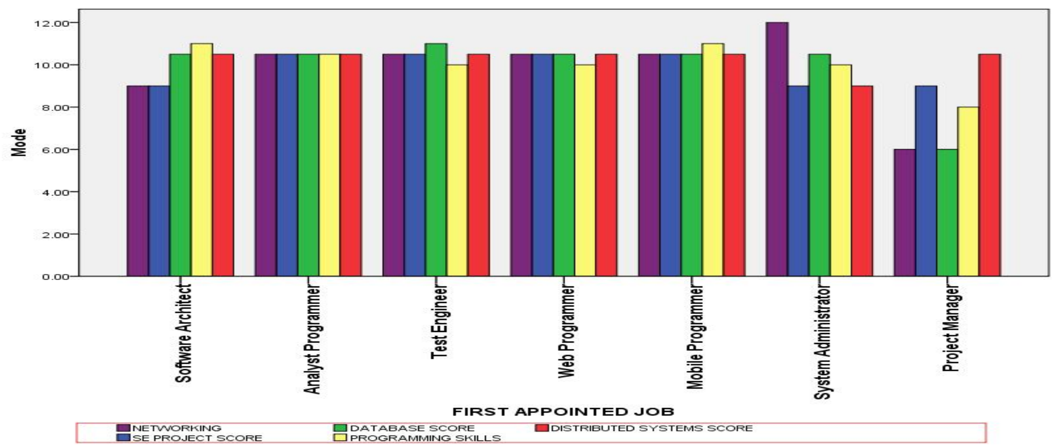


Fig. 4i. Average technical skills required to perform each industry role

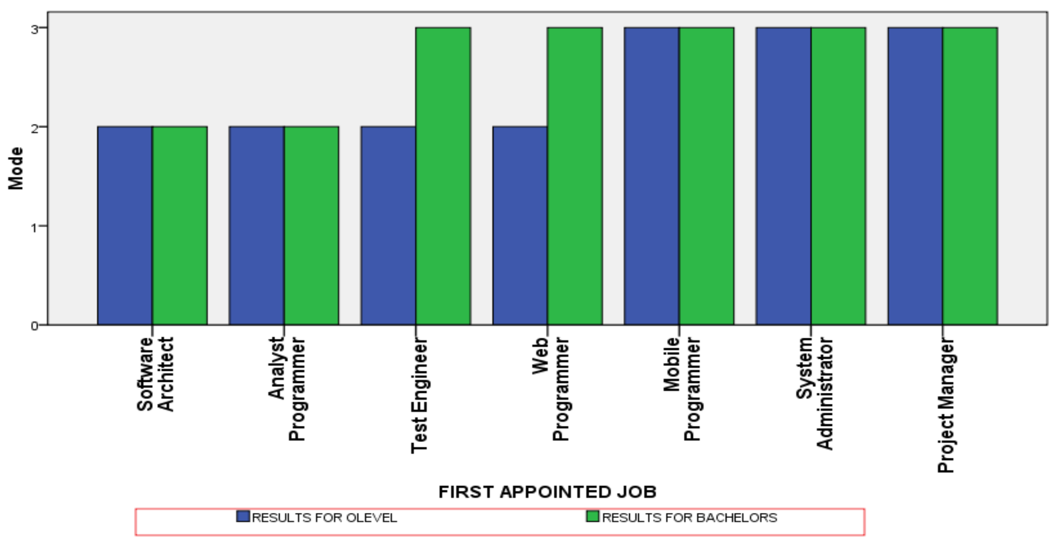


Fig. 4j. Average Intellectual capacity required to perform each industry role

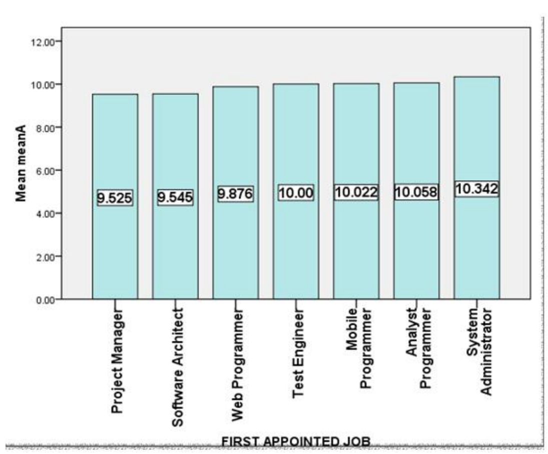


Fig. 4k. Average accuracy index required for each industry role

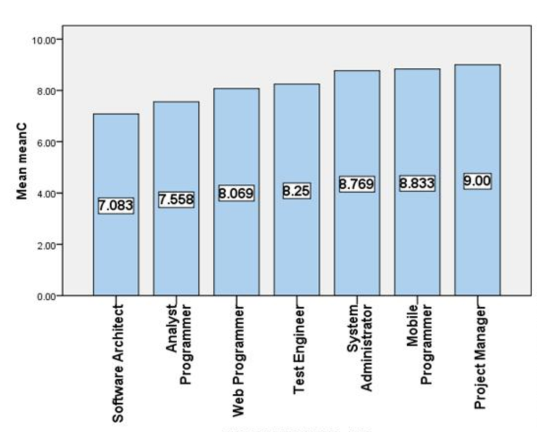


Fig. 4l. Average capacity index required for each industry role

Table 2a. Tests of hypotheses results (Test Statistics[b])

Index type	N	Median	Chi-Square	df	Asymp.Sig
meanC(Capacity)	109	-.0525	16.151[a]	6	.013
meanA(Accuracy)	109	.0464	1.866[a]	6	.932
meanD(Durability)	109	-.0005	13.109[a]	6	.041
meanR(Relevance)	109	.0279	2.441[a]	6	.875

a. 4 cells (28.6%) have expected frequencies less than 5. The minimum expected cell frequency is 2.0.
b. Grouping Variable: FIRST APPOINTED JOB

3.5.1 RQ1: Are there significant differences in knowledge and skills among various industry roles?

To approach this research question, the four main qualitative variables were classified into two different ways with the help of a 2 by 2 matrix. One way was to classify them as either knowledge (Relevance & Capacity) or skill type (Accuracy & Durability) and the other way was to classify them as either domain specific (Relevance & Accuracy) or general (Capacity & Durability). After that, each of the two original research hypotheses was split into two to give four new research hypotheses to be investigated in order to answer this research question:

Hypothesis 1(H_{01}):

> H_0: There are no significant domain specific knowledge differences between industry roles in the same occupation
> H_a: There are significant domain specific knowledge differences between industry roles in the same occupation

For this hypothesis, relevance variable (meanR) was used as the test variable and we reject the null hypothesis when the test statistic value (*P*) is less than significance value (.05), otherwise we accept the null hypothesis. Table 2a presents test statistic results (χ^2=2.44, *P*=.87) and therefore we accept the null hypothesis that there is no significant difference.

Hypothesis 2(H_{02}):

> H_0: There are no significant domain general knowledge differences between industry roles in the same occupation
> H_a: There are significant domain general knowledge differences between industry roles in the same occupation

For this hypothesis capacity variable (meanC) was used as the test variable and we reject the null hypothesis when the test statistic value (*P*) is less than significance value (.05), otherwise we accept the null hypothesis. Table 2a presents test statistic results (χ^2=16.15, *P*=.01) and therefore we reject the null hypothesis and accept the alternative hypothesis that there is significant difference.

Hypothesis 3(H_{03}):

> H_0: There are no significant domain specific skill differences between industry roles in the same occupation
> H_a: There are significant domain specific skill differences between industry roles in the same occupation

For this hypothesis accuracy variable (meanA) was used as the test variable and we reject the null hypothesis when the test statistic value (*P*) is less than significance value (.05), otherwise we accept the null hypothesis. Table 2a presents test statistic results (χ^2=1.86, *P*=.93) and therefore we accept the null hypothesis that there is no significant difference.

Hypothesis 4(H_{04}):

> H_0: There are no significant domain general skill differences between industry roles in the same occupation
> H_a: There are significant domain general skill differences between industry roles in the same occupation

For this hypothesis durability variable (meanD) was used as the test variable and we reject the null hypothesis when the test statistic value (*P*) is less than significance value (.05), otherwise we accept the null hypothesis. Table 2a presents test statistic results (χ^2=13.10, *P*=.04) and therefore we reject the null hypothesis and accept the alternative hypothesis that there is significant difference.

Finally, the hypothesis testing results were appended in the two way classification table as shown in Table 2b and interpreted as: while there is no significant difference in domain specific knowledge and skills among various industry roles in the same occupation, there is indeed significant difference in domain general knowledge and skills among the industry roles.

Table 2b. Hypothesis testing results

Variable type	Knowledge	Skill
Domain specific	Accept	Accept
Domain general	Reject	Reject

3.6 Trend Analysis towards Industry Roles

Fig. 5a presents bar graph results showing comparison of average Relevance Index values while Fig. 5b presents bar graph results showing comparison of average Durability index values for various universities in the academia both derived from their exam past papers. Results reveal although 'KCA' university has the highest relevance index, its durability index value is the lowest. While 'UON' university has the highest durability index value, 'JKUAT' university has the lowest relevance index value.

3.6.1 RQ2: what are the trends in knowledge and skills in the academia towards industry roles?

In order to reveal trends in academia towards industry roles, a simple approach was adopted consisting of plotting both inter-quartile range (between 25th percentile and 75th percentile as the measure of dispersion) for each industry role and the index values for each university on the same box-plot graph. The index values were super-imposed on the box-plot using reference lines and a reference line touching any industry role's quartile box or above its upper quartile mark was considered as a trending industry role for that particular university. Fig. 5c shows box-plot results of the Relevance index requirements for various industry roles represented using boxes and Relevance index values for various universities represented using reference lines. The results reveal that while universities 'KCA' and 'UON' are trending in all industry roles, 'JKUAT' is only trending in only three industry roles i.e. 'software architect', 'mobile programmer', and 'project manager'.

Fig. 5d shows box-plot results of the Durability index requirements for various industry roles and Durability index values for various universities represented using reference lines. The results reveal that only 'UON' is trending in all industry roles, while 'KCA' and 'EGERTON' are only trending in only one and two industry roles respectively i.e. 'analyst programmer' for 'KCA', while for 'EGERTON' are 'analyst programmer', and 'web programmer'.

Table 3 presents a summary of the counts of the trending industry roles in each university as revealed by Figs. 5a and 5b analysis results.

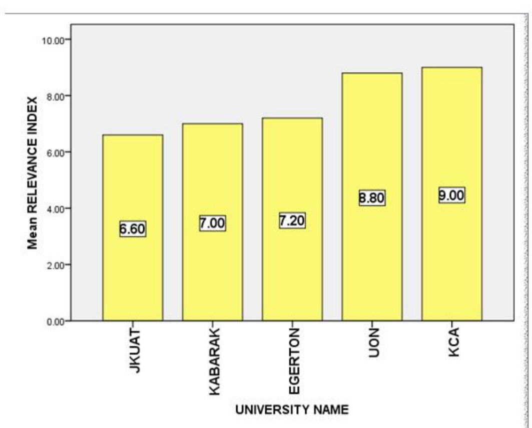


Fig. 5a. Relevance Index derived from academia

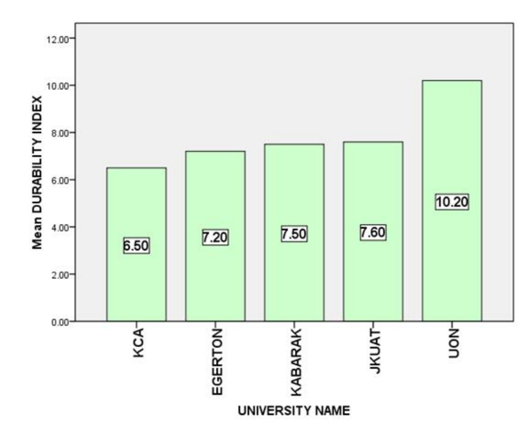


Fig. 5b. Durability Index derived from academia

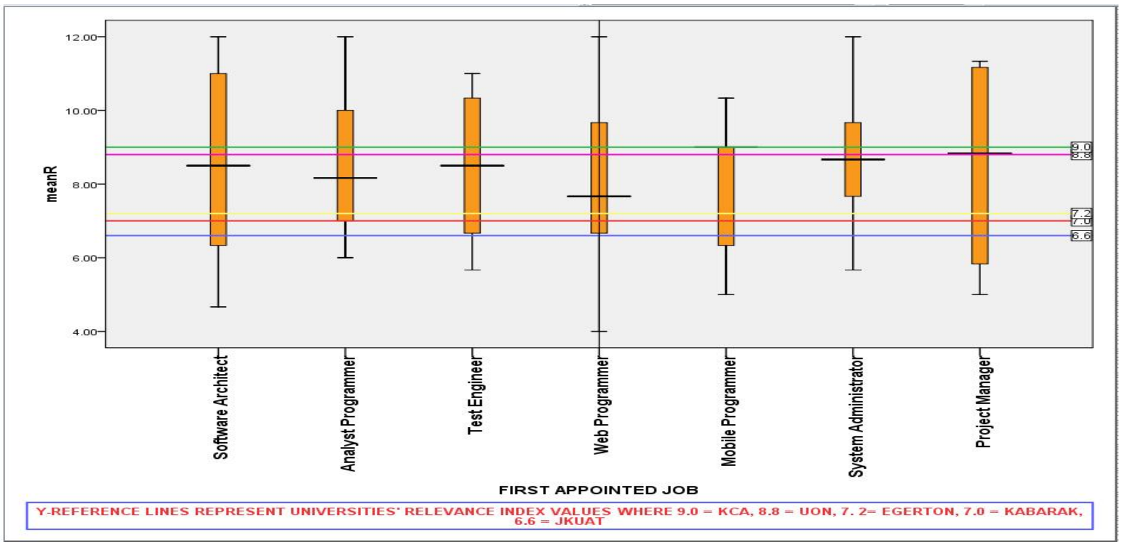


Fig. 5c. Comparison of average relevance index of academia and industry roles

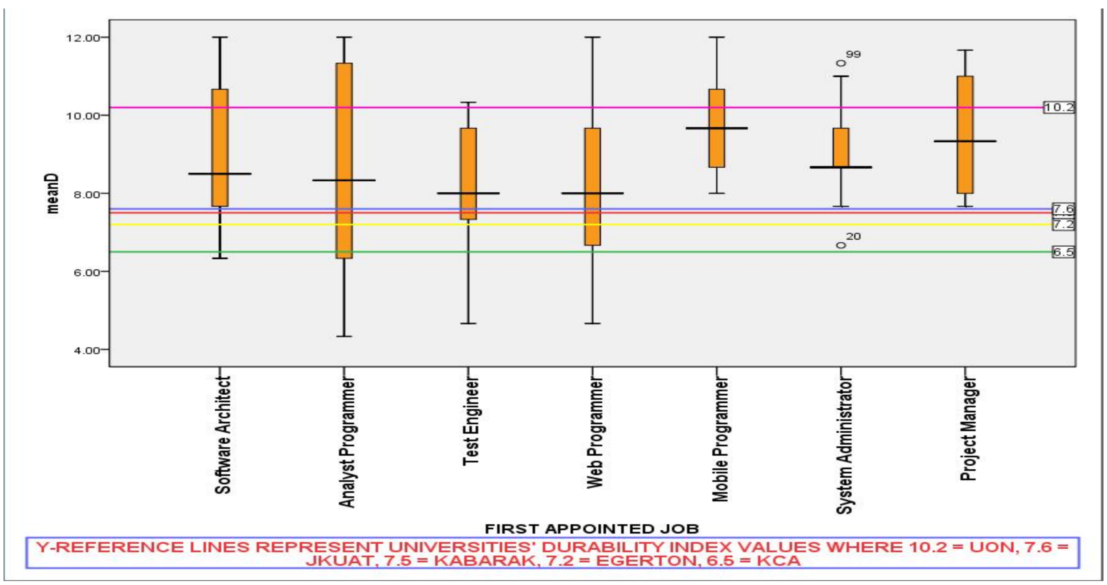


Fig. 5d. Comparison of average durability index of academia and industry roles

Table 3. Summary of trending industry roles in the academia

University name	Counts of roles in Relevance Index	Counts of roles in Durability Index	Average counts per university	Percentage (%)
1. UON	7	7	7	100%
2. JKUAT	3	3	3	42.9%
3. Kabarak	6	3	4.5	64.3%
4. Egerton	5	2	3.5	50%
5. KCA	7	1	4	57.1%
Average counts per variable	5.6	3.2		
Percentage (%)	80%	45.7%		62.86%

3.7 Discussion

The key objective of this paper was to evaluate industry roles requirements and learning trends in the academia towards industry roles using the proposed model for mapping graduate's skills to industry roles. The overall aim is to improve graduates' employability by investigating factors that improve their performance productivity in the industry. This study extends the findings of other researchers [25,23] and especially that of Shkoukani [9], by showing that factors such as core content knowledge, cognitive skills, technical skills, and intellectual capacity can help reveal academia trends towards industry roles and greatly promote prediction of graduates' productivity and employability. The findings revealed: 1) Table 1b indicates qualification is least considered by graduates as a means for choosing industry roles and majority (67.9%) of them feel exams expose at least 75% of classroom learnt content. This causes skill mismatch problem and concurs with other findings that reveal industry dissatisfaction with graduates performance [9,19], 2) Fig. 2 and 3 indicate industry roles with elements of management activities are not popular at job entry level and perhaps the reason being management roles demand working experience. This concurs with other studies that suggest entry-level positions are most relevant to graduates from bachelors programs and therefore any study that purports to promote productivity and employability of new graduates should concentrate on these entry level positions [23], 3) Figs. 4d and 4k and Table 2b indicate domain specific knowledge and skills for industry roles in the same occupation are similar. Perhaps many bachelors programs are designed to target a wider sector of the job market hence ending up with a complicated mix of skills that is difficult to match with industry role requirements [3,4,6]. Although studies [23] suggest strategies to respond to this is for academia to specialize in certain skill groups or sectors of the job market, this may reduce employability chances for graduates by narrowing the pool for industry roles they can qualify, 4) Figs. 4h and 4l and Table 2b reveal domain general knowledge and skills are significantly different for industry roles in the same occupation. Domain general knowledge and skills are associated with problem-solving skills, and therefore, this finding is in agreement with [18,11], that requirements thresholds for problem solving skills vary differently for different jobs and therefore the issue is to know the precise levels for each. And lastly, 5) Fig. 3a to 3d reveal academia trends towards various industry roles within the same occupation are not uniform among universities, and Table 3 reveal that in terms of domain specific knowledge academia is trending very well towards occupational industry roles(80%) but poorly in terms of skills (45.7%). Therefore, the study concludes that academic knowledge and skills requirements for industry roles in the same occupation are not similar and although knowledge trends are fairly good, skill trends towards these industry roles are poor.

4. CONCLUSION AND RECOMMENDATIONS

4.1 Conclusion

Therefore, the study concludes that academic knowledge and skills requirements for industry roles in the same occupation are not similar and although knowledge trends are fairly good, skill trends towards these industry roles are poor.

4.2 Recommendations

Based on the above research findings, there are several implications and recommendations both to the academia and industry as follows: 1) domain specific knowledge and skills must be covered well during learning in the academia because they are key in providing graduates with sufficient foundation for performing all types of occupational industry roles, 2) because becholor's curriculum is the source of domain specific knowledge and skills in the academia, it must be approved by domain experts and stakeholders both in industry and academia, 3) industry should not judge the capacity of a graduate to perform a job based on the content of the approved degree program but both qualifications and university of study, 4) academia should carefully select undergraduate students with minimum intellectual capacity demanded by various industry roles, 5) academia should emphasize the right levels of thinking skills during training, 6) industry should select graduates from regulator certified degree programs in those occupations and assign them industry roles based on their qualifications, lastly, 7) students should select universities that have a higher trending profile for industry roles in order to increase their employability chances.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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