An Integrated Employability Aptitude Survey-Cognitive Test Model for Assessing Students' Skills Retention Threshold

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Abstract. An integrated employability aptitude survey-cognitive test is proposed to assess the retention threshold of students with the view of appraising the capabilities of engineering students in readiness for engineering positions. Numerical ability, space visualization, numerical reasoning, and symbolic reasoning responses are adapted into the model. One hundred six undergraduate students of the Department of Industrial Engineering at Eastern Mediterranean University selected across freshman, sophomore, junior and senior in the 2016–2017 academic years assessed their aptitudes through the proposed EAS cognitive tests. Analysis of variance is employed to analyze the model, and the results indicate a significant difference between students' abilities in terms of raw scores and respective academic levels. Academic years and CGPA groups are found to have significant effects on the student's percentile. Additionally, strong correlations between CGPA and the student's percentile are found. However, space visualization ability is not affected by academic progression.

Keywords: Aptitude · EAS-cognitive tests · Student's percentile · Skills retention threshold · Battery score

1 Introduction

The new economy characterized by technology and globalization has led to the creation of a high-wage; highly skilled and high-changing jobs that are demanding new skill sets from graduates. This continually brews various concerns for graduate employability. Psychological discoveries have specifically revealed that for engineering skills gained during studies to be retained, knowledge garnered have to be embedded functionally, engraved in professional behavior, applied tactfully and in realistic contexts, and must be demonstrated through achievable and practical skills and values. Quite often, rate of retention and its threshold have been examined and determined through some widely reported concepts such as general cognitive ability (GCA), cognitive ability tests (CAT), general mental ability (GMA), just to mention a few. Schmidt (2002) has shown that there

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is a link between GCA and job performance. More often, experience have shown that the level of job performance is a function of the retainability (amount of knowledge learned that could be readily recollected and leveraged to satisfy the job skill requirements) and its threshold (the amount of skills and knowledge retained that could serve appreciably and adequately as basis for meeting the minimum skill requirements). Similar to GCA, many researchers concluded that CAT also correlates highly with job performance (Bobko *et al.* 1999 and Schmidt et *al.* 1997).

Cognitive or mental ability is the prime determining factor of job performance that dictates the dynamics of employability. Over time the impact of cognitive ability on performance is expected to continue to rise (Schmidt et *al.* 1981). Tests such as the GMA and CAT have been employed in the past decades to assess the mental and cognitive ability of employee during the selection process (2002). CAT tends to produce significant racial variances; similarly, Hunter and Hunter (1984), Schmidt and Hunter (1999) and Sackett et al. (2001) through various studies confirmed the efficiency of GMA as a valid means of evaluating employee empirically. The performance and effectiveness of employees have been evaluated by the newly introduced general aptitude test battery (GATB) (Bobko et al. 1999). This cognitive ability is calculated as the raw score (RS), which is the combination of general, verbal, and numerical (G, V, N) aptitude scales of the GATB. The EAS, a kind of GMA test, has been developed to assess the psychomotor, perceptual, and cognitive capabilities, mainly for the selection of employees, career guidance, development, and advancement. Retention acts as the fulcrum on which students' ability to re-create and apply skills gained are pivoted (Hodges *et al.* 2013).

The main aim of this article is to emphasize the essence of cognitive skills for employment-driven skills development during academic learning. Furthermore, the significance of EAS in promoting skills retention and threshold toward a successful job engagement is of utmost interest of this study. EAS consists of different ten (10) tests that can be employed separately, and the choice of any test is guided by the user's assessment of the job requirements (Ruch 1994). This study assesses the array of abilities through four of the Employee Aptitude Survey EAS tests to develop battery and percentile models for monitoring students' progression and efficiency. This provides a new frontier for assessing the retention rate of students right from freshman to senior year. Thus the readiness and propensity of graduates for employability are easily evaluated.

2 Methodology

2.1 Instrumentation: Employee Aptitude Survey (EAS)

EAS was used for assessing the capabilities of engineering students as required by the junior engineering positions. Four EAS tests were selected out of ten as the requirements to determine the students' battery and percentile for appraising their progression between different academic years. These tests are numerical ability (EAS-2), space visualization (EAS-5), numerical reasoning (EAS-6), and symbolic reasoning (EAS-10).

2.2 Procedures for Data Gathering

Approval was secured from the Ethics committee to administer the tests to the students. Permissions were also taken from the instructors to apply the EAS tests on the students during lecture hours. At least 40 min is required to complete the four tests; each test takes 5 min. The numerical ability test (EAS-2) is in three parts, and it requires ten minutes to complete. A 3–5-min break was allowed in-between the two tests. Instructions on how to complete the tests are written clearly on the front page of the sheet. Additionally, some personal information about the students such as age, CGPA, and Cumulative Credit Hours (Cum. CH) relevant to this study were extracted from the student registration database.

2.3 Participants

One hundred six undergraduate students of the Department of Industrial Engineering at Eastern Mediterranean University between the age of 17 and 30 years old across all academic levels (Freshman, Sophomore, Junior and Senior) took part in this study conducted during both fall and spring semesters of the 2016–2017 academic session. The students were examined during the following lectures; Introduction to IE (IENG112), Modeling and Optimization (IENG212), Operations Research-I (IENG313), Fundamentals of Work Study and Ergonomics (IENG301), Production Planning-II (IENG431), Systems Modeling and Simulation (IENG461). These lecture sessions were chosen because they are available for experimentation and comprises of students from all academic levels. The following research questions were addressed:

(i) Do academic advancements have significant effects on engineering students' abilities?
(ii) Which of the students' abilities (numerical ability, space imagining, numerical reasoning, and symbolic reasoning) is affected by these academic levels?
(iii) Does the age of the students have any significant effect on the students' percentile?
(iv) Is there any correlation between CGPA and percentile?

Analysis of variance (ANOVA) was employed to analyze responses from these questions.

2.4 Calculation of the Raw Scores, Battery and Percentile

The raw score is defined as the number of questions responded to by the participants without considering the number of questions on the test or each question point. The total number of answers marked wrong and right were recorded. It should be noted that each test has different RS formulas. The battery score is determined through the following formula:

$$\text{Battery Score } = 0.5 * (\text{EAS } 2) + 0.5 * (\text{EAS } 5) + \text{EAS } 6 + \text{EAS10} \tag{1}$$

The percentile for each student was determined from the norm table of junior engineer (Ruch 1994). For the statistical analysis, variables were defined as independent and dependent. The dependent variable is the students' percentile, while the independent variables are academic years, CGPA groups, and age groups. To protect the students' privacy, codes A to D were assigned to all students instead of their student numbers. Normality assumptions were examined using the normal test, frequency histograms, and normal plot of residuals. Minitab 17 statistical package was employed for the analysis.

3 Results

The results show that normality assumptions are not violated, and thus confirming the data are normally distributed. Consequently, ANOVA with (α = 5%) is a suitable test to be used for the data analysis. The mean, standard deviation, maximum, and minimum values of students' percentile are listed in Table 1.

Table 1. Descriptive statistics of students' percentile

Source	Variables	Count	% students	Mean	St.Dev	Min	Max
Gender	F	30.00	28.30	37.90	22.31	2.00	80.00
	M	76.00	71.70	28.39	19.97	1.00	80.00
Age groups	<=22	45.00	42.45	29.80	19.87	1.00	60.00
	23–25	52.00	49.06	33.21	22.91	1.00	80.00
	26–28	7.00	6.60	26.43	11.44	15.00	40.00
	>=29	2.00	1.89	21.0	26.9	2.00	40.00
Academic year	Freshman	13.00	12.26	13.69	11.52	1.00	40.00
	Sophomore	29.00	27.35	18.86	16.12	1.00	50.00
	Junior	37.00	34.90	34.19	18.20	5.00	70.00
	Senior	27.00	25.47	48.33	18.45	10.00	80.00
CGPA groups	<=1.99	29.00	27.36	11.62	10.82	1.00	40.00
	2–2.49	24.00	22.64	27.50	14.89	5.00	60.00
	2.5–2.99	17.00	16.04	36.76	16.48	15.00	70.00
	3–3.49	16.00	15.09	48.75	12.04	30.00	80.00
	>=3.5	15.00	14.15	56.00	13.52	30.00	80.00
	Newstudent	5.00	4.72	10.60	12.18	1.00	30.00

Students who got the highest total cumulative credit hours and CGPA greater than 3 recorded the maximum value of the percentile of 80. From the raw score, the results of numerical ability with academic level show a significant effect (*p-value = 0.000*). Additionally, the Tukey test reveals the numerical ability of the senior students is significantly different from other academic levels. These results connote that students' numerical ability differs and it is a function of academic years. The rank is from the senior level with the largest value of raw score of 42.50 to freshman level with the smallest value of mean raw score = 27.52. Therefore, the higher the academic level, the better the numerical tendency of students.

For space visualization ability EAS-5 test, there is no significant difference (*p-value* = 0.074) between different academic levels. However, there is a significant difference between academic years and numerical reasoning EAS-6 test at (*p-value* = 0.008) based on the students' raw scores. Similarly, the Tukey test shows that senior-level students have the highest numerical reasoning score. For symbolic reasoning, EAS-10 test, a significant difference (*p-value* = 0.000) between academic years is observed. This test entails how students can easily decipher mathematical symbols and expressions. The multiple comparison tests reveal higher symbolic reasoning ability as the academic year progresses. The result shows that there is a significant effect between students' academic years and students' percentile (p-value = 0.00). However, students' age does not have any significant effect on student' percentile (p-value = 0.07). This implies that age would not influence the estimation of the response (percentile) given in Table 2.

Table 2. General linear model: percentile versus academic years and age

Factor	Type	Levels	Values			
Academic year	fixed	4	Freshman, Junior, Sophomore, Senior			
Age	fixed	4	<=22, 23-25, 26-28, >=29			
Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**
Academic year	3	16654.3	18023.7	6007.9	21.54	0.000
Age	3	2034.0	2034.0	678.0	2.43	0.070
Error	99	27611.9	27611.9	278.9		
Total	105	46300.2				

A general linear model is used to examine the interrelationships between student's percentile, academic levels, and CGPA. However, the freshman level is ignored. This is because most of the new students (freshman) do not have CGPA. The ANOVA shows that there are significant effects (*p-value* = 0.000) of students' academic years on the percentile scores. It can be well said that these scores significantly vary with the CGPA groups at (*p-value* = 0.000). However, the interaction between CGPA groups and academic levels does not have any significant effect on the percentile scores of students (*p-value* = 0.69), as shown in Table 3.

Furthermore, correlation analysis conducted among the percentile scores and students CGPA illustrates a large correlation between students CGPA grades and percentile scores (r = 0.752). According to Cohen (1988) and Kim (2018), a correlation value greater than 0.5 is described as large; 0.5 to 0.3 as moderate, 0.3 to 0.1 as small; and anything smaller than 0.1 is described as being trivial; variables of such trivial relationships have no noticeable relationships.

Table 3. General linear model: percentile versus academic year and CGPA

Factor	Type	Levels	Values			
Academic year	fixed	3	Junior, Sophomore, Senior			
CGPA group	fixed	5	<=1.99, 2-2.49, 2.5-2.99, 3-3.49, >=3.5			
Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**
Academic year	2	12172.1	3547.2	1773.6	11.79	0.000
CGPA groups	4	15483.4	12963.1	3240.8	21.54	0.000
Academic year*CGPA	8	833.6	833.6	104.2	0.69	0.697
Error	78	11736.1	11736.1	150.5		
Total	92	40225.2				

4 Discussion and Conclusion

This study investigated the skills retainability of IE students as they progress academically through the years of studies relative to their ages and CGPA. The findings show that the ability of students improves as the students advance in their academic studies. This is in agreement with the finding of Brockman and Russel (2012), where a positive relationship between academic level and the abilities of the students was reported. As the student progresses in their academic endeavors, they are better equipped with all the necessary knowledge and skills; thus, senior students have superior abilities than junior and freshman students. Therefore, retention of skills increases proportionally with an academic level even as the abilities of students improves as the academic studies advances.

Additionally, aligning with another study of Cassidy (2007), the academic level is of the essence in determining students' retainability. Especially for freshman, attrition is because of a lack of the ability to understand how their personal dimension for learning could influence the capacity for proper adaptation into the university study. This explains how the perception of their external world could translate into knowledge or belief (Jama et al. 2008).

The study also reveals no relationship between academic years and space visualization. This result is similar to what was reported by Kozhevnikov and Thornton (2006) that students' levels of spatial visualization ability are based on physics training within the confinement of the microcomputer-based laboratory (MBL). The space visualization prediction of students' performances is not significantly affected by the level of the instructions given to the students. This accounts for the poor disposition of educators toward emphasizing this skill in the curriculum. For numerical reasoning, senior students have the highest scores. The results obtained in this study is akin to the results obtained elsewhere (James 2015) where literacy (mathematics, writing quality and comprehension) was used as an indicator for success in the skills for Tertiary Education Preparatory Studies (STEPS) program.

The EAS tests reveal students' percentile is not significantly affected by students' age. Ebenuwa-Okoh (2010) also reported that age, gender, and financial status do not seem to cause any significant difference in academic performance. Therefore, counseling should be provided for students of all ages, financial status, and gender. Similarly, the results of this study are in-line with that of Hodges et al. (2013) where age was reported to have an insignificant effect on student's academic capabilities. This has cast doubts on the functionality of age as a variable that can effectively influence the academic capabilities of a student. This also inferred beyond doubt that there is no significant relationship between students' age and academic ability. Therefore based on the EAS tests, relationships exist between CGPA groups and percentile, and between percentile and academic levels. Hence, as students advance academically year-on-year, they acquire more skills and can score higher percentile on the EAS tests. Consequent on this, it could infer that retainability increases as the academic level progresses. This is also in tandem with some previous studies on students' attrition (see Gabb et al. 2006; Jones 2008 and Rose-Adam and Lindsay 2012; Winne and Nesbit 2010) where various ways of improving retention have been reported.

The average percentile of students that studied in the fourth year is larger than those that studied in the previous academic years. This research has explored the effects of academic years and CGPA. This is discovered to have some significant effects on student abilities. Here, we have concentrated on the importance of academic progression in improving students' abilities. Skills such as numerical ability, numerical reasoning, and symbolic reasoning have been identified. Thus, it demonstrates that graduate students from the industrial engineering department of Eastern Mediterranean University have higher retainability of skills, and thus possesses greater propensity and readiness to take on the responsibility of the workplace. The outcome of space visualization test indicates student's ability does not improve as the academic level progresses; thereby; all students irrespective of their academic level possess this ability close to each other.

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