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Undergraduate Students' Intelligence Profiles According to the Tes Intelligensi Kolektip Indonesia Tinggi (TIKI-T): A Cluster Analysis Based on the Rasch Model Person Ability

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Abstract

This research aims to identify undergraduate students' intelligence profiles using a two-stage cluster analysis based on the person's ability of the Rasch model to examine the effect of the clusters on academic performance. A total of 1443 undergraduate students from nine academic disciplines at Universitas Padjadjaran in Bandung, Indonesia, participated in the study, completing 11 subtests of the Tes Intelligensi Kolektip Indonesia Tinggi (TIKI-T). A hierarchical cluster analysis approach using Ward's linkage method and squared Euclidean distance was conducted, followed by a nonhierarchical k-means cluster analysis using simple Euclidean distance as the similarity measure to examine two-, three-, four-, and five-cluster solutions. An intra-class correlation (ICC) and a discriminant analysis were also conducted to validate the cluster membership results. This research identified five profiles of intelligence that had an effect on academic performance. Students with high scores in the scholastic aptitude subtests tended to have higher grade point average than those with high scores in the nonverbal ability subtests and the speed and accuracy ability subtests. The findings can be used as a recommendation for psychologists in Indonesia for university placement tests.

Profil Kecerdasan Mahasiswa Berdasarkan Tes Intelligensi Kolektip Indonesia Tinggi (TIKI-T): Analisis Klaster berdasarkan *Person Ability* dari Model Rasch

Abstrak

Penelitian ini bertujuan untuk mengidentifikasi profil kecerdasan dari mahasiswa dengan menggunakan dua tahap analisis klaster berdasarkan *person ability* dari model pengukuran *Rasch* dan melihat dampak dari profil tersebut terhadap prestasi akademik. Sebanyak 1443 mahasiswa dari sembilan program studi di Universitas Padjadjaran di Bandung Indonesia menyelesaikan sebelas kelompok soal dari TIKI-T. Pendekatan Hierarki dengan metode *Ward's Linkage and Square Euclidean distance* dilakukan, diikuti oleh non-hierarki analisis klaster dengan dua, tiga, empat dan lima solusi klaster sebagai pembanding. Analisis *intra-class correlation (ICC)* dan analisis diskriminan juga digunakan untuk memvalidasi keanggotaan dari setiap klaster. Penelitian ini mengidentifikasi lima profil kecerdasan yang berpengaruh terhadap prestasi akademik. Ditemukan bahwa mahasiswa dengan nilai yang tinggi dalam kelompok soal yang mengukur kemampuan skolastik cenderung mendapatkan hasil yang lebih baik dalam prestasi akademik dibandingkan dengan mahasiswa yang memiliki nilai tinggi dalam kelompok soal yang mengukur kemampuan nonverbal ataupun tinggi dalam kelompok soal yang mengukur kecepatan dan ketepatan. Temuan ini dapat digunakan sebagai rekomendasi bagi psikolog di Indonesia untuk tes penempatan universitas.

Keywords: academic performance, cluster analysis, intelligence profile, the TIKI-T

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1. Introduction

Intelligence is related to performance in a wide range of cognitive tasks and is one of the best predictors for educational and professional success (Buschkuehl & Jaeggi, 2010; Rosander, Bäckström, & Stenberg, 2011; Schmidt & Hunter, 1998). Research in educational settings has revealed that intellectual factors obtained from psychometric tests have medium to high correlations with students' academic performance. For instance, Mackintosh (1998) found that the correlation between IQ and school performance grade ranged from 0.40 to 0.70. Additionally, a national survey conducted by Deary, Thorpe, Wilson, Starr, and Whalley (2003) in the United Kingdom discovered that general intelligence had an enormous contribution to 25 academic subjects for 11-year-old students with correlations ranging from 0.43 to 0.77. However, the relationship was higher when the latent intelligence traits (Spearman's g of a psychometric test) and the latent traits of educational performance were correlated.

The range of findings in intelligence research including university students have tended to relate to the level of the correlation coefficient. Busato, Prins, Elshout, and Hamaker (2000), for instance, found that the minimum correlation between intelligence and academic performance in psychology students was only 0.13. A light to moderate relationship was also found in general university students (Komarraju, Ramsey, & Rinella, 2013). It should be emphasized that the correlation between IQ and academic performance for university students was lower than that for junior and elementary school students. This trend was related to the restriction range of university students who are selected on more specific criteria (Chamorro-Premuzic & Furnham, 2005).

The findings mentioned above focus on the global capacity of the intellect in academic performance, otherwise known as "g factor" (Spearman, 1904). However, a lot of research has been conducted to discover the specific factors, or "s-factors," that influence students' attainment in school such as working memory (Weber, Lu, Shi, & Spinath, 2013), numerical ability (Halberda, Mazzocco, & Feigenson, 2008), and verbal ability (Lee, Ng, Ng, & Lim, 2004). More specifically, research has tended to focus on one subject only (e.g., mathematics) instead of academic performance as a whole (Landerl, Bevan, & Butterworth, 2004; Landerl & Moll, 2010).

Another approach to predict academic performance from intelligence is the use of cognitive profiles. A profile approach provides an alternative way of representing students' intelligence by including information about the combinations of multiple constructs and the constructs' respective magnitudes. By using a profile approach, it is possible to identify which profiles relate to high academic performance and which relate to low academic performance (Letteri, 1980). A profile approach can thus help identify possible learning deficits.

To identify profiles based on intelligence factors, several studies have been conducted in both educational and occupational contexts: Amthauer (1970) identified intelligence profiles based on nine subtests in the Intelligenz Struktur Test from people who were successful in various kinds of jobs; Letteri (1980) proposed a cognitive profile that related to seven dimensions of the cognitive test for seventh and eighth grade students; Kim, Frisby, and Davison (2004) explored the cognitive profiles of Woodcock–Johnson Psychoedu-cational Battery; and both Bergeron and Floyd (2013) and Mayes and Calhoun (2004) investigated the cognitive profiles of children with disabilities.

In the Indonesian population, Djunaidi and Suryabrata (1997) investigated intelligence profiles based on 11 subtests of the Tes Intelligensi Kolektip Indonesia Tinggi (TIKI-T) (Drenth, Dengah, Bleichrodt, Soemarto, & Poespadibrata, 1977) from a university student sample in Yogyakarta, Indonesia. The 11 subtests measured several constructs of cognitive abilities, and the results identified four intelligence profiles of the university students. The first profile had a high contribution from the visualization, components, hidden figures, number series, and spatial orientation subtests. The accuracy and speed, arithmetic, and verbal analogies subtests highly contributed to the second profile. The third profile was influenced by the figure classification subtest. Finally, the fourth profile was only influenced by the word relations subtest. Nevertheless, no evidence was found that related the effect of the intelligence profile to academic performance, and the analysis was based on the calculated scores that used the classical test theory approach.

Similar to the above mentioned study (Djunaidi & Suryabrata, 1997), this research is also focused on university students' intelligence profiles according to the TIKI-T (Drenth et al., 1977). The most appropriate procedure to define natural groupings within data is through a cluster analysis (Hair, Black, Babin, Anderson, & Tatham, 2014; Mooi & Sarstedt, 2011) which is a multivariate procedure to identify groupings within data. A cluster analysis of variables resembles a factor analysis because both procedures detect related groups of variables (Hair et al., 2014). In this study, cluster analysis was used to identify the naturally occurring profiles or groups of students within a sample that has a similar pattern of scores on the 11 subtests of the TIKI-T. Unlike previous study, however, the present study applies a Rasch Model analysis to the calculation of the scores (Rasch, 1960).

The Rasch analysis, originally developed by George Rasch, is a part of the item response theory. Rasch (1960) proposed a mathematical model based on the relationship between the probabilities of a student's response to an item as a function of the student's "ability." The Rasch model for dichotomous data is appropriate to analyze multiple choice items that are scored as either right or wrong. The Rasch analysis provides more advantages than the classical test theory (CTT) employed in Djunaidi and Suryabrata's (1997) study. One limitation of CTT is that the item and person characteristics are dependent on each other. This means that item parameters (e.g., item difficulty) might change depending on the subpopulation considered in the study (i.e., test items could appear easy when the test is administered on a high ability subpopulation, and vice versa). The Rasch model analysis overcomes this limitation by allowing the formulation of item characteristics and the personal abilities by distinctive parameters, such as sample invariants (Bond & Fox, 2015). The Rasch analysis also provides a transformation of an ordinal score into an interval level variable where valid scores and access to parametric statistics are required (Tennant & Conaghan, 2007). Another advantage of the Rasch analysis is related to its assumption of *unidimensionality*: by assuring the *unidimensionality* of the test, its construct validity will be supported, allowing for adequate theoretical interpretations of the test score (Van der Ven & Ellis, 2000). The Rasch model has been widely used to analyze and develop several cognitive tests (Ariffin et al., 2010; Freitas, Prieto, Simões, & Santana, 2014; Koski, Xie, & Finch, 2009; Primi, 2014; Woodcock, 1999; Woodcock, McGrew, & Mather, 2001). The research questions for the current study were therefore: (1) What are university students' intelligence profiles based on the Rasch person ability? (2) Does academic performance differ based on the intelligence profile?

2. Methods

Sample and Participants. 1443 undergraduate students from 9 academic disciplines at Universitas Padjadjaran in Bandung, Indonesia, participated in the study. The study programs were randomly selected from more than 50 disciplines. There were 338 animal husbandry students (23.4%), 266 psychology students (18.4%), 206 Sundanese literature students (14.3%), 181 biology students (12.5%), 158 pharmacy students (10.9%), 91 geological engineering students (6.3%), and 76 international relations students (5.3%); the remaining students were studying library sciences (4.5%) and sociology (4.5%). The majority of the participants were first-year (40%) and second-year (48%) students, and only 116 (1.50%) were third-year students. According to gender classification, more than half of the participants were women, 966 (66.9%), and the rest were males, 477 (33.10 %). The mean age of the participants was 19.34 years (SD=0.91).

Participation in the study was voluntary. Several procedures were conducted before collecting the data. First, the researcher explained the aim of the study and the process of the data collection to the target students. Second, the informed consent forms were collected from the students as an agreement for their participation in the study. Third, the data was collected in a classroom setting with 60–100 students in a room. The tests were administered by experienced instructors, with the assistance of three to five co-instructors. All the processes were conducted under the supervision of psychologists. The time used for a single administration was 90–120 min. Lastly, the participants received a reward after finishing the test.

Measures. The primary data used in this study was obtained from the TIKI-T. The TIKI-T consists of 11 subtests in a multiple-choice format with four to five options. Each subtest measures a different construct, and each has a different number of items and time limits. Based on the test manual (Drenth et al., 1977), the test specifications for each subtest are as follows:

- *Arithmetic* (α = 0.96). This subtest consists of 40 items that measure the ability to solve simple numerical problems that require arithmetic operations, such as addition, subtraction, multiplication, and division. The time limit for this subtest is 7 min.
- *Component* (α = 0.88). This subtest consists of 26 items that measure the ability to manipulate and transform figural material. The time limit for this subtest is 7 min.
- *Word relations* (α = 0.90). This subtest consists of 40 items that measure the ability to identify two words with either identical or contrasting meanings. The time limit for this subtest is 5 min.
- *Figure classification* (α = 0.81). This subtest consists of 30 items that measure the ability to classify figural objects. The time limit for this subtest is 12 min.
- *Number series* (α = 0.64). The subtest consists of 20 items that measure the ability to find a number in a series of numbers arranged according to a certain principle. The time limit for this subtest is 10 min.
- *Accuracy and speed* (α = 0.88). The subtest consists of 100 items. The test requires the speed and accuracy to identify identical or different words. The time limit for this subtest is 4 min.
- *Visualization* (α = 0.84). This subtest composes 30 items that measure the ability to visualize three-dimensional figures from two-dimensional figures. The time limit for this subtest is 5 min.
- *Spatial orientation* (α = 0.98). The subtest consists of 40 items that measure the ability to rotate an object and reflection from the initial figure. The time limit for this subtest is 10 min.
- *Verbal analogies* (α = 0.53). The subtest consists of 18 items that measure deductive reasoning. The time limit for this subtest is 4 min.
- *Hidden figure* (α = 0.76). The test contains 20 items that measure the ability to search a distracting perceptual field to find a given configuration. The time limit for this subtest is 6 min.

- *Word composition* (α = not reported). The test contains 60 items that measure the ability to find the missing letters of a frequently used word. The time limit for this subtest is 4 min.

The secondary data collected was related to academic performance (grade point average—GPA). The range of the students' GPA was from 0.00 to 4.00. An analysis of performance (ANOVA) found that there was a significant difference in average GPA among the nine academic disciplines. Therefore, for the analysis, the GPA scores were converted into Z-scores based on the mean and standard deviations for each academic discipline.

Analyses. Several procedures were used to analyze the data. Firstly, the Rasch model analysis for dichotomous data was conducted to acquire the person ability scores. This model was appropriate for analyzing the multiple-choice items which are scored as either right or wrong (Rasch, 1960). The person ability scores represent an estimate of a person's underlying ability related to his/her performance on a set of items that measure latent traits (Bond & Fox, 2015). In the analysis, person ability estimates were computed using weighted likelihood estimates (WLEs) for dichotomous responses (Warm, 1989). The Rasch model analysis has several important requirements, specifically model fit or item fit, *unidimensionality*, and local dependency (Bond & Fox, 2015).

Two scores were used to evaluate the item fit: Infit mean square (MNSQ) and outfit MNSQ. However, outfit MNSQ is an unweighted score which is more sensitive to outlier responses (Bond & Fox, 2015), and therefore in the present analysis only infit MNSQ values were used to evaluate the misfit items. Items with infit MNSQ statistics between 0.75 and 1.30 were included in the next analysis (Bond & Fox, 2015). The dimensionality of the TIKI-T was assessed using a principal component analysis (PCA) of the residuals. According to Linacre (2006), variance explained by measures of more than 60% and unexplained variance by first contrast of less than 5% could be taken as initial indicators of *unidimensionality*. However, Sumintono and Widhiarso (2015) recommended another criterion of dimensionality: a subtest with more than 40% variance explained by measures and less than 15% unexplained variance is accepted as having *unidimensionality*, whereas more than 60% variance explained by measures is considered as having excellent *unidimensionality*. Lastly, local dependence is important to evaluate the independency of one datum in relation to another datum, that is, the value of one datum has no influence on another datum. High correlation, whether positive or negative, is an indicator of local dependency for any pair of items (Wright, 1996). Cohen (1988) stated that high correlation can be indicated by a correlation coefficient greater than 0.5. The analyses for the Rasch model in this study used Conquest software. Except for examining PCA and local items dependence, the Winstep software was used, as this analysis was available in Conquest software.

Secondly, screenings for univariate and multivariate normality and outliers were conducted. Descriptive statistics (i.e., mean, standard deviations, and bivariate correlations) were analyzed to provide a description of the sample. Bivariate correlations were computed because they were important to examine multicollinearities. Hair et al. (2014) explained the effect of multicollinearity to the cluster analysis as a form of implicit weight. To examine multicollinearity, a review of the correlation matrix was conducted. According to Field (2009), correlation coefficients between variables should not exceed 0.80. The results are shown in Table 1.

Thirdly, the exploration of the cluster from the data was conducted using a two-stage cluster analysis. The first stage is the hierarchical cluster analysis using Ward's method and squared Euclidean distance. Ward's minimum variance method produced the most reliable results. Ward's algorithm has been commonly used in intelligence studies because it has performed quite well in comparison to alternative clustering methods (Donders, 1996; Hale, Casey, & Ricciardi, 2014). This method is appropriate to obtain the same approximate size of samples as the cluster group. The range of profiles was explored by reviewing the agglomeration schedule coefficient from two-, three-, four-, or five-cluster solutions which is acceptable to interpret. The process continued with a nonhierarchical k-means cluster analysis using simple Euclidean distance. This k-means specified a two-, three-, four-, or five-cluster solution. This approach is recommended to correct fusion errors that random cluster centers can produce (Hair et al., 2014). To review the reliability, the cluster membership by hierarchical and k-means, an intraclass correlation coefficient (ICC), was computed to acquire the index of cluster "stability" (reliability) of the two methods (Morris, Blashfield, & Satz, 1981). Thus, all prospective solutions were compared on the basis of association between the results from the hierarchical and the k-means.

Cohen's Kappa statistics and one-way random effects ICC were used to compare the solutions in terms of membership agreement and profile similarity, respectively. Higher reliability index of the cluster solutions was chosen for further analysis. For the external validation, this study used discriminant analysis, also known as supervised classification of some observations, to classify others (Hair et al., 2014). This method was used to assess whether or not a set of variables discriminates between the cluster groups by k-means method. Discriminant function coefficients as the

Table 1. Descriptive Statistics and Correlation Matrices for the Study Variables (N = 1368)

Subtest		1	2	3	4	5	6	7	8	9	10	11
1	AR	1										
2	CO	0.263	1									
3	WR	0.317	0.285	1								
4	FC	0.443	0.438	0.379	1							
5	NS	0.514	0.305	0.329	0.466	1						
6	AS	0.206	0.194	0.146	0.203	0.172	1					
7	VI	0.337	0.464	0.293	0.510	0.358	.193	1				
8	SO	0.368	0.355	0.282	0.494	0.406	.143	0.431	1			
9	VA	0.291	0.205	0.260	0.380	0.343	.147	0.286	0.301	1		
10	HF	0.314	0.364	0.254	0.458	0.333	.161	0.388	0.367	0.265	1	
11	WC	0.259	0.237	0.229	0.280	0.261	.168	0.226	0.254	0.189	0.251	1
Original *N*-item		40	26	40	30	20	100	30	40	18	20	60
Mean (WLE score)		1.674	1.527	.891	0.974	0.320	.894	1.680	0.748	0.153	1.194	3.690
SD		0.937	1.104	0.934	.385	.359	.176	1.111	2.055	0.857	1.488	1.039

***Note*: AR**, arithmetic; **CO**, component; **WR**, word relation; **FC**, figure classification; **NS**, number series; **AS**, accuracy and speed; **VI**, visualization; **SO**, spatial orientation; **VA**, verbal analogy; **HF**, hidden figure; **WC**, word composition. Values in italics indicate *p* < 0.01 (two-tailed). *p<0,05; **p < 0,01

results from the discriminant analysis showed the best predictor on the dependent variable. The dependent variable for this analysis was the clustered group, while the independent variables were 11 subtests of the TIKI-T. The coefficients were standardized to remove the effects of differences between mean and standard deviations.

The final analysis for this study focused on which profiles were the best predictor of academic performance. A one-way ANOVA was conducted using the k-means cluster analysis profile groups as the independent variable and the standardized GPA as the dependent variable.

3. Results

Rasch analysis. The Rasch model analysis for the item fit is presented in Table 2. The better an item was, the closer it was to the model fit. The results show that more than half of the TIKI-T subtests had items with infit statistics within the accepted range 0.75 and 1.30 (Bond and Fox, 2015). Only arithmetic (8%, three items), figure classification (7%, two items), accuracy and speed (66%, 66 items), spatial orientation (5%, two items), and word composition (23%, 14 items) had items with infit MNSQ outside the accepted range. All those items were excluded from the following analysis. The data show that "accuracy and speed" and "word composition" had the highest number of items excluded from the subtest. These subtests measure speed ability: how fast a person does a simple task using cognitive automatic processing. The analysis for such a subtest should be based on the frequency distribution rather than solely using the item analysis.

Table 3 shows that all subtests had more than 40% variance explained by measures, which ranged between 40% (verbal analogies) and 82% (accuracy and speed). All subtests had less than 15% unexplained variance on first contrast, which ranged between 2% (word composition) and 6% (number series). This means that all TIKI-T subtests meet the *unidimensionality* requirement. Meanwhile, according to Wright (1996) and Cohen (1988)'s criteria for local item dependence, only two subtests "accuracy and speed" and "word composition" had items with correlation coefficient greater than 0.50.

Both subtests had a high percentage variance explained (82% and 72%, respectively), yet showing high local

Table 2. Infit and Outfit Statistics from Rasch Model Analysis

Subtest	% of items excluded	Infit MNSQ				Outfit MNSQ			
		Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Arithmetic	8	0.97	0.17	0.71	1.40	2.29	1.79	0.54	6.74
Component	0	0.98	0.07	0.84	1.14	1.32	0.47	0.83	2.77
Word relation	0	0.99	0.11	0.76	1.29	1.10	0.39	0.64	2.47
Figure classification	7	0.99	0.14	0.72	1.43	1.08	0.38	0.60	2.21
Number series	0	1.00	0.09	0.85	1.13	1.35	0.81	0.79	3.69
Accuracy and speed	66	0.89	0.33	0.53	2.63	6.35	4.10	0.36	9.90
Visualization	0	0.98	0.11	0.78	1.17	1.28	0.67	0.45	3.76
Spatial orientation	5	0.96	0.14	0.75	1.32	1.98	1.81	0.68	9.90
Verbal analogies	0	1.00	0.06	0.91	1.13	1.02	0.19	0.72	1.52
Hidden figures	0	1.00	0.10	1.00	1.27	1.14	0.34	1.14	1.90
Word composition	23	0.94	0.20	0.61	1.49	4.42	3.67	0.36	9.90

Table 3. Dimensionality and Local Dependence Analysis

Subtest	Dimensionality		Local dependence	
	% variance explained	% unexplained variance in first contrast	Largest standardized residual correlation range	Indication of local dependence
Arithmetic	63	3	0.37 to 0.23	No
Component	51	5	–0.19 to 0.40	No
Word relation	53	4	0.31 to 0.22	No
Figure classification	41	3	–0.15 to 0.21	No
Number series	40	6	–0.21 to 0.16	No
Accuracy and speed	82	3	1.00 to 0.93	Yes
Visualization	53	4	–0.17 to 0.15	No
Spatial orientation	59	3	0.36 to 0.20	No
Verbal analogies	40	5	–0.19 to –0.13	No
Hidden figures	45	5	–0.12 to 0.12	No
Word composition	72	2	0.81 to 0.39	Yes

dependency. The effect of item independence is inflating the ability estimates of items at a given scale. Moreover, it seriously distorts the qualities of the items (Sideridis, 2011). However, in this research, items with high correlations were also misfit items. Thus, such items were excluded in cluster analysis.

Descriptive statistics. Data screening procedures did not identify any variables as non-normal (skewness/kurtosis > 2), but 65 univariate outliers were found ($z > \pm 3.0$). Therefore, those cases were excluded for the following analysis. This is important because outliers can have a significant impact on the results, particularly in cluster analysis (Hair et al., 2014).

Table 4. Group Descriptive Statistic and Test Equality for Estimation Sample in the Three-Group Discriminant Analysis

Independent variable	Dependent variable group mean (*Z*-score from the WLE)					Test of equality of group Means		
	1st Cluster (*n* = 186)	2nd Cluster (*n* = 283)	3rd Cluster (*n* = 300)	4th Cluster (*n* = 135)	5th Cluster (*n* = 464)	Wilks' Lambda*	*F*	Sig.
Arithmetic	–0.97	0.70	0.08	–0.92	0.34	0.60	226.22	0.00
Component	0.08	0.86	–0.57	–1.27	0.28	0.56	268.22	0.00
Word relation	–0.48	0.68	0.00	–0.96	0.23	0.73	125.59	0.00
Figure classification	–0.79	0.94	–0.25	–1.25	0.41	0.46	404.65	0.00
Number series	–0.95	0.75	–0.03	–1.03	0.37	0.58	251.41	0.00
Accuracy and speed	0.07	0.60	–0.16	–0.69	0.01	0.86	55.01	0.00
Visualization	–0.31	0.90	–0.33	–1.37	0.29	0.55	281.54	0.00
Spatial orientation	–0.59	0.83	–0.39	–1.21	0.42	0.57	261.75	0.00
Verbal analogies	–0.68	0.56	0.13	–0.89	0.24	0.73	128.07	0.00
Hidden figures	–0.39	1.05	–0.34	-1.00	0.12	0.61	217.44	0.00
Word composition	–0.04	0.63	–0.43	-0.88	0.28	0.76	109.52	0.00

Note: *Wilks' Lambda (*U*-statistic) and univariate *F* ratio with 4 and 1363 degrees of freedom

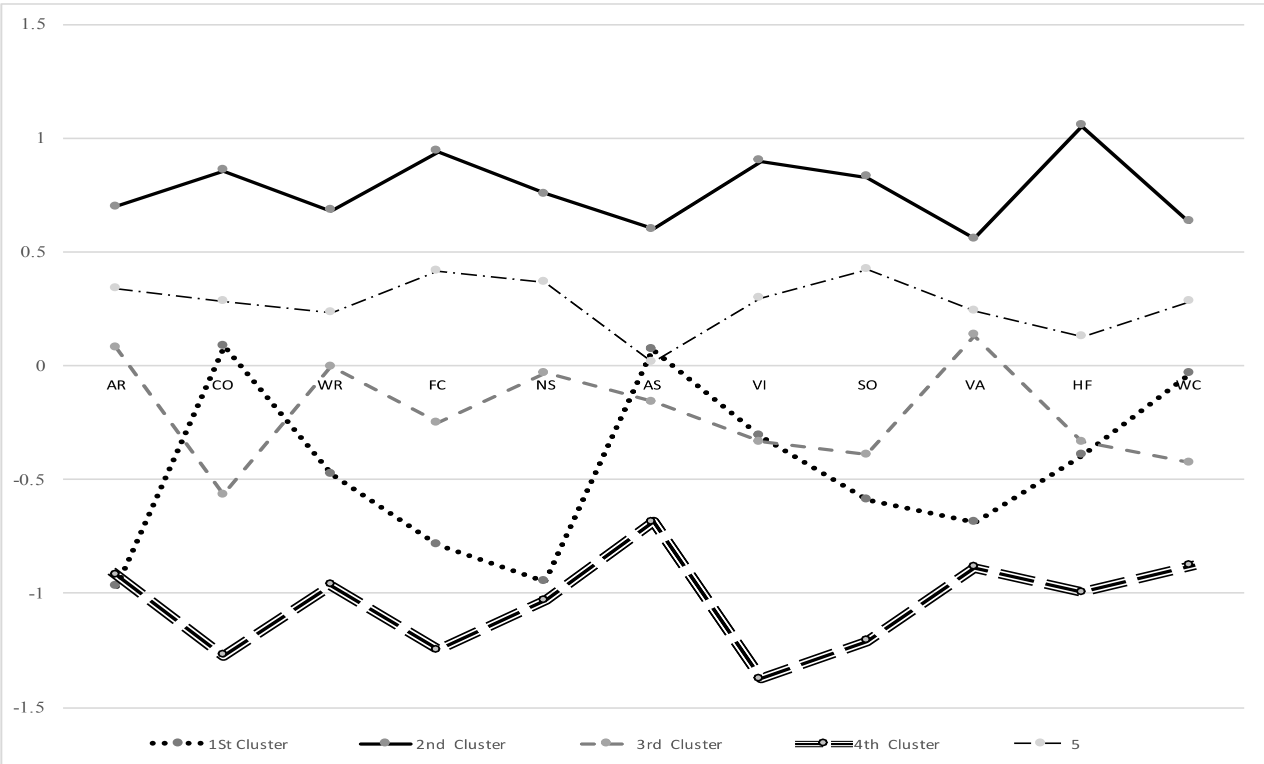

Figure 1. Results of the k-means Cluster Analysis using WLE Scores. AR, Arithmetic; CO, Component; WR, Word Relation; FC, Figure Classification; NS, Number Series; AS, Accuracy and Speed; VA, Visualization; SO, Spatial Orientation; VA, Verbal Analogy; HF, Hidden Figure; WC, Word Composition

Cluster analysis. Cluster analysis. The reliability of the three-, four-, and five-cluster solutions were evaluated by comparing the profiles acquired from the initial Ward's analysis (first stage) to those derived from the k-means analysis (second step). The ICC for the five-cluster solution was −0.679 (p = 1.00), for the four-cluster solution was 0.164 ($p < 0.05$), and for the three-cluster solution was 0.405 ($p < 0.05$). These results indicated that the three- and four-cluster solutions were less stable, whereas the five-factor solution was the most stable. Therefore, the five-cluster solution was chosen for a discriminant analysis.

The group descriptive statistic and test equality are presented in Table 4. Significant mean differences were observed for all the predictors on the dependent variable. The Z-score from WLE person ability for the second cluster was the highest for all independent variables. It indicated that the students in the second cluster had the highest intelligence factor. The log determinants were quite similar between −5.532 and 6.567. The Box's M indicated that the assumption of equality of covariance matrices was violated. However, because the sample size was large, this was not an indication of a problem. The discriminate function revealed a significant association between groups and all predictors. A canonical correlation of 0.938 suggests that the model explains 87.9% of the variation in the grouping variable, that is, whether the student grouped into the first, second, third, fourth, or fifth cluster. The cross-validate classification showed that 94.4% were correctly classified, which indicated that the classification from the cluster analysis process was valid.

Description of clusters. The five clusters generated based on the k-means analysis were assigned descriptive labels reflecting the most salient features of each mean (WLE) from the TIKI-T profile. Figure 1 illustrates the mean of each subtest on the TIKI-T for every cluster profile using the standardized WLE scores. This information was provided to aid the interpretation and labeling of the profiles. The labels were used to characterize the profiles relative to their counterparts. In this case, they mostly corresponded to high and low levels of the students on each subtest. From Figure 1, the first profile (dotted line) was labeled as *below average level of intelligence factors* (n = 186) as it was generally represented by a level of intelligence profile between 0 and −1. This profile had the highest score in the component subtest, speed and accuracy subtest, and word composition subtest. The second profile (straight line) was labeled as *high level of intelligence factors* (n = 283) as this profile was characterized by a high level of all intelligence factors. The third (dashed line) was labeled as *average level of intelligence* factors. The third profile (dashed line) was labeled as average level *of intelligence factors* (n = 300) as it was generally represented by intelligence ability that was relatively neither too high nor too low compared to the other clusters. This profile was also characterized by the highest score on both the arithmetic and visualization subtests. The fourth profile (bold dashed line) was labeled as *low level of intelligence factors* (n = 135) as it was visualized by the lowest intelligence score for every subtest. The fifth profile (dashed-dotted line) was labeled as *above average level of intelligence* (n = 464) as this profile was characterized by a relatively high level of all intelligence factors. Almost one-third of the samples were classified in this profile.

Table 5 presents the membership proportion for the nine academic disciplines. Overall, the disciplines were classified into three major groups based on the proportion in each cluster. The first group were psychology, pharmacy, and geological engineering students. In these academic disciplines, more than 65% of the students were categorized as followed by *average level of intelligence*, and only a few portions of the students with a *low level of intelligence factors*. The second group were biology, animal husbandry, international relations, and sociology students. The majority of the students in these academic disciplines were classified as possessing an *average and above average level of intelligence factors* (55–60%), followed by *high level of intelligence* (10–25%), and the rest as a *low and below average level of intelligence factor*. The third group were composed of students studying library science and Sundanese literature. In these disciplines, 55–60% students were categorized as possessing *low and below average level of intelligence factors,* followed by average ability students, and less than 10% of students were categorized as possessing a *high level of intelligence factors*.

Intelligence profile and academic performance. A one-way between-groups analysis of variance was conducted to explore the impact of intelligence profiles on GPA and IQ deviation. As mentioned previously, the GPA was standardized to minimize the effect of mean differences between the academic disciplines.

Meanwhile, IQ deviation was a standardized score with the mean 100 and SD 15. Participants were divided into five groups according to the level of intelligence profile: Group 1, *low level of intelligence*; Group 2, *below average level of intelligence*; Group 3, *average level of intelligence*; Group 4, *above average level of intelligence*; and Group 5, *high level of intelligence* there was a statistically significant difference at the $p < 0.05$ level in standardized GPA scores for the three groups intelligence profiles: F (4, 1342) = 6.425, $p < 0.01$. Despite reaching statistical significance, the actual difference in the mean scores between the groups was quite small. The effect size, calculated using etasquared, was only 0.019. With equal variance not assumed, post-hoc comparisons using Dunnett' C-test indicated that the

Table 5. The Membership Proportion for Each Cluster Based on Academic Discipline

Cluster	Study program									
	1	2	3	4	5	6	7	8	9	Total
1 (%)	3.10	3.20	6.30	10.30	13.90	16.40	24.10	27.10	37.20	13.60
2 (%)	35.20	30.40	23.30	27.60	12.70	26.00	10.30	8.50	4.40	20.70
3 (%)	21.10	21.50	29.50	17.20	26.30	20.50	19.00	11.90	15.60	21.90
4 (%)	1.90	3.20	7.40	3.40	11.40	0.00	19.00	27.10	25.60	9.90
5 (%)	38.70	41.80	33.50	41.40	35.80	37.00	27.60	25.40	17.20	33.90

Note. Academic discipline: 1, psychology; 2, pharmacy; 3, biology; 4, geological engineering; 5, animal husbandry; 6, international relations; 7, sociology; 8, library science; 9, Sundanese literature.

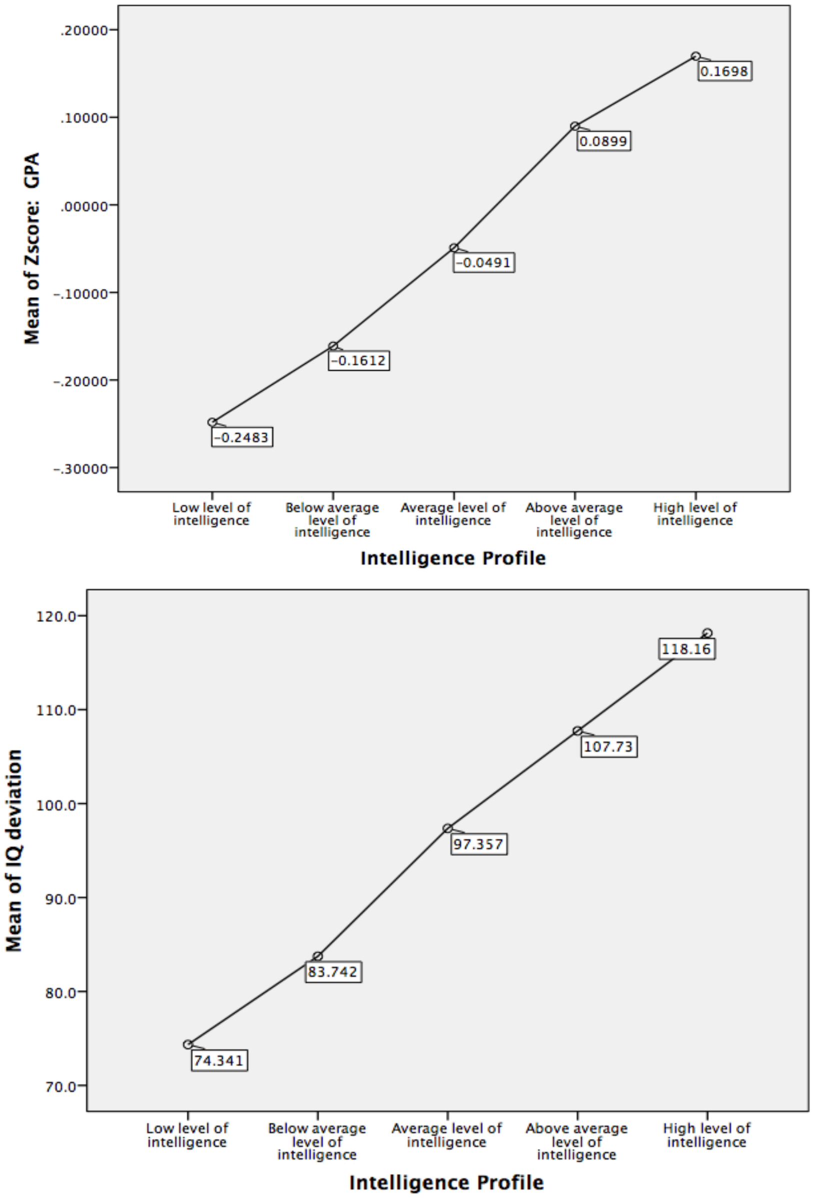

Figure 2. The Relation of Intelligence Profile with GPA and IQ

mean score for Group 5 (M = 0.170, SD = 0.884) was significantly different from Group 1 (M = –0.248, SD = 1.060), Group 2 (M = –0.161, SD = 1.168), and Group 3 (M = –0.049, SD = 0.971) and did not differ significantly with Group 4 (M = 0.090, SD = 0.96). There was a significant difference between Group 4 with Groups 1 and 2. There was no significant difference found between Group 2 and Group 3; between Group 2 and Group 4; and between Group 3 and Group 4. Details of mean differences are shown in Figure 2.

4. Discussion

The results suggest that reliable intelligence profile patterns of the TIKI-T subtest scores can be derived using cluster analysis for undergraduate students. This study found that students from the nine academic disciplines showed variations in both level and pattern of performance across the TIKI-T subtests. Although previous research discovered four clusters in the undergraduate student samples (Djunaidi & Suryabrata, 1997), there were five clusters obtained in the present investigation based on k-means clusters analysis, with the highest ICC compared to three- and four-cluster solutions. The five clusters were highly correlated with IQ deviations. This finding explained a high correlation between g factor and s factors (Spearman, 1927). In other words, the level of the subtest scores was a reflection of the IQ deviation.

The terms used in the labels of the clusters were similar to the levels of intelligence in the Differential Ability Scales Second Edition (DAS-II; Urbina, 2011). In DAS II, the categorizations are low (IQ level 70–79), below average (80–89), average (90–109), above average (109–120), and high (120–129). In this research, there was a slight difference in the level of IQ for the categories above average and high. The majority of the students could be grouped into above average level of intelligence (33.90%), with the top three subtests being figure classification, number series, and spatial orientation which measure nonverbal reasoning abilities (Drenth et al., 1977). The second largest majority of students were clustered into the average level of intelligence (21.90%), with the top three subtests being arithmetic, verbal analogies, and word relations which mainly measure the general scholastic aptitude (Drenth et al., 1977). Although a large majority of students were grouped into high level of intelligence (33.90%), the hidden figure, figure classification, and visualization subtests were shown as the top three subtests. In the below average level of intelligence group (13.60%), the top two subtests were word composition and accuracy subtests. These subtests measured speed and accuracy abilities (Drenth et al., 1977). The cluster with the smallest proportion of students was the low level of intelligence (9.90%). Similar to the below average level of intelligence group, the top two subtests were word composition and accuracy subtests which measure speed and accuracy abilities (Drenth et al., 1977). Based on these results, the students with high scholastic aptitude tended to have higher GPAs than those with high nonverbal abilities and high speed and accuracy abilities.

This study has several implications for psychologists who use the TIKI-T as an instrument for student placement or career guidance. First, the study has demonstrated the use of cluster analysis for investigating the intelligence profiles of the TIKI-T. From the cluster analysis, it should be highlighted that the cluster of the TIKI-T did not divide students based on their academic discipline due to the similar proportion of students in each cluster. Moreover, no specific intelligence profile was found for each academic discipline. However, psychologists may find that the intelligence profiles found in this study can be used as a basis for the prediction of students' academic performance. To identify students' abilities, psychologists should take a look at intelligence profiles based on the score of individuals and categorize them into high level of intelligence, average level of intelligence, and low level of intelligence. Students with a high level of intelligence have a good opportunity to succeed in academic disciplines with high learning demands. In the present research, these disciplines included psychology, geology engineering, and pharmacy. On the other hand, individuals with a low level of intelligence would be better suited to a less demanding discipline for a greater chance of good performance. Moreover, the identification of students with lower TIKI-T scores may be useful for designing learning interventions and preventing further academic problems. Besides, psychologists also have to consider the scholastic aptitude scores of each individual in making a decision as this score contributes to the GPA score.

This study has some limitations that need to be highlighted. First, the use of the cluster analytic method. Even though multiple methods were used to validate the cluster membership, cluster analysis represents a relatively subjective research tool (Lange, Iverson, Senior, & Chelune, 2002). The results from the analysis will be different each time a different sample is used. Second, regarding the similarity coefficient, the method of distance was used in this research, and association indices followed conventional standards and were empirically driven. In the end, the researchers' knowledge and theoretical background should be adequate (Hale et al., 2014). Third, this study used person ability estimates from the Rasch model. However, in the analysis, the scores were transformed into Z-scores to justify that all the variables had the same distance. Moreover, several data were also indicated as outliers. Therefore, the results from the Rasch analysis was approximately normal and unbiased except for the extreme abilities, which are consistently biased toward the mean by a floor and ceiling effect (Pelton, 2002). A comparative study needs to be conducted to justify the different results between the

Rasch model and CTT. Finally, this study provides a basis for future research on the interpretation of the TIKI-T intelligence profiles. The findings of this study do not provide evidence for the use of TIKI-T intelligence profile for the prediction of student performance across different academic disciplines, thus further study may be needed to provide the basis for profile interpretation of the TIKI-T according to specific academic disciplines.

5. Conclusion

This paper contributed to the literature by outlining the two stages of cluster analysis: the first step was hierarchical and the second step was a k-mean cluster analysis for profiling intelligence and analyzing the effect of the profile to academic performance. The two methods used were ICC and discriminant analysis which were conducted to justify the membership of the respondents. This paper also contributed to the identification of which factor in the intelligence profile contributed to academic performance. These results may be used by psychologists to identify and predict undergraduate candidates' academic performance.

Declaration of Interest

The authors report no conflicts of interest in this work.

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