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FACTORS AFFECTING THE QUALITY OF STUDENTS' RESEARCH WORK: EXPLORING THE PERCEPTION OF STUDENTS

Emmanuel Benson
Department of Mathematics and Statistics, School of Applied Science, Takoradi Polytechnic, Takoradi

Kwabena Nduro
Department Of Graphics, School of Applied Arts, Takoradi Polytechnic, Takoradi

Eric Kwadwo Amissah
Department of Graphics, School of Applied Arts, Takoradi Polytechnic, Takoradi.

ABSTRACT: *There is a growing debate focused on the quality of students' project work at Takoradi Polytechnic. There is a general consensus that the quality of students' project work are declining. However, what constitutes quality is undefined within this debate neither factors that influence quality. Opinions regarding factors which determine the quality of research are, in the main, driven by anecdotes and not concrete facts. Our objective was to identify the factors influencing the quality of project works from the perception of students. The statistical technique used in analysing the data for this study was Exploratory Factor Analysis (EFA) which yielded five factors comprising only half of the original number of items presented to students to which they were to respond. The extracted items constituting the five factors are thus important corollary for fashioning policies for addressing issues of quality with respect to students' project work.*

KEYWORDS: Factors, Students' Perception, Polytechnic, Project Work, Quality Research

INTRODUCTION

As part of the requirement for graduating, students are obliged to undertake project works. This fulfills a partial condition for the conferment of a degree at any level of the tertiary educational spectrum including HND degrees. The purpose for this is at least broadly two fold. Firstly, it allows students to undertake independent work. Secondly, specialized skill sets and knowledge are acquired. But merely acquiring expert knowledge and specialized skills would not by themselves be enough in ensuring quality research by students. Indeed, an unambiguous understanding of what quality means and what the sources of quality are in the context of research would be critical in the writing of quality research work.

There is a growing debate focused on the quality of students' project works at Takoradi Polytechnic. There is a general consensus that the quality of students' project works are declining. However, what constitutes quality is not defined within this debate neither factors that influence quality. Thus, examining a few definitions of quality as well as drivers of quality research work at this stage would suffice.

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LITERATURE REVIEW

From the perspective of Fink (1998), research must have certain key elements or features to qualify as quality research. In his view, a research work is deemed to be of quality if it has an "internally and externally valid research design, reliable data sources, free from plagiarism, application of appropriate tools, and meaningful interpretation of results in practical and statistical terms". Ranjit (2009) on the other hand, argues that quality research work "must be controlled, rigorous, systematic/structured, valid and verifiable, empirical and critical". Clearly, from the foregoing definitions, the common thread running through these definitions is that quality research can only be assured if it is valid in terms of methodology, practical relevance and verifiability. We can achieve this if we "focus on the quality of the content of the thesis, quality of the research process and quality of research management (Mahmood, 2011). However, it must be noted that, in all of this, the perceptions and experiences of students must form an integral part of the raised voices in the quality debate and by extension policy to resolve the purported decline. Otherwise, we may simply be embarking on a wild goose chase.

Another angle to the quality debate which we alluded to earlier is the factors influencing the quality of students' project work from the point of view of students. Opinions regarding factors which determine the quality of research are, in the main, driven by anecdotes and not concrete facts. For the purposes of good scholarship, however, Andresen (2000) suggests we go beyond this and collect the evidence for our own evaluation. Exploring these factors via the perceptions of students holds practical relevance in the sense that it brings to the fore the opinions of a key stakeholder in the quality assurance space. In this way, astract and far fetched reasons are not ascribed to why the quality of students' project work is falling. Consequently, policy formulated using such student driven information is likely to impact positively any declining trend in students' research. To identify factors perceived by students to matter as far as the quality of their research work is concerned we examined some studies (e.g. Mahmood, 2011; Isani and Virk, 2005). According to Isani and Virk (2005), the quality of research is linked, either directly or indirectly, to the quality of the teachers, research courses, supervision of research and the facilities. Mahmood (2011) posited similar factors.

Thus, we adopted and adapted these factors and extended them by including the project student as a potential influencer of project quality in this present study.

Exploring these factors a little further would throw more light on the subject. Barnet (1992) draws parallel between effective teaching and the research experience of the teacher. He argued that for teaching to be effective, one must have been involved in research. According to Barnet, for research to be beneficial academically, it should be linked to the curriculum because "the more they work in areas which underpin the curriculum, the less is the intellectual distance between teaching and research activities". In that sense, such a linkage could potentially make the teacher a better teacher in the sense that, it improves his/her subject matter knowledge, develops the course as well as elevate his/her supervisory capability Rowland (1996). Indeed, Rowland concludes "that closer relationships between the two can form the basis for a programme to improve the quality of university teaching". What does these assertions suggest? What it means is that, the quality of the teacher caused by his/her research experience has an effect on a number of the other factors posited by Isani and Virk (2005). Thus, focusing on improving the relevant research capability of the teacher could have a positive knock on effect on these factors which by extension may improve the quality of students' research activities. However, improving the quality of the teacher though

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important, will also require a complimentary provision of facilities such as computers, softwares, journals, well stocked library among others in a systemic manner.

Our objective in this study is to identify the factors influencing the quality of project works from the perception of students.

METHODOLOGY

The statistical method used in analysing the data for this study is Exploratory Factor Analysis (EFA) which is extensively used in a vast array of contexts (Costello and Osborne, 2005; Basto and Pereira, 2012). It is a multi-stage procedure which seeks to "identify the underlying factors that explain the pattern of correlations within a set of observed variables" (Basto and Pereira, 2012). In other words, fundamentally, factor analysis is used to "reveal any latent variables that cause the manifest variables to covary" (Costello and Osborne, 2005). Panter, Swygert, Dahlstrom, & Tanaka (1997) also describe the procedure as factor analysis of the latent variables which underlie the raw ordinal data and are assumed to be continuous and normally distributed rather than on the Pearson correlations matrix.

A major pitfall which tends to undermine results of factor analysis and has become a major source of contention is the treatment of ordinal variables as continuous variables. This has been shown to be inappropriate. On the basis of this, Bernstein and Teng (1989) contend that because factor analysis is suitable for variables which are continuous and multivariate normal, analyzing ordinal level data, which does not obviously meet such criteria, would be erroneous and problematic. To address this data presented limitation, O'Connor (2000) and Basto and Pereira (2012) suggest that factor analysis be conducted on the polychoric correlations matrix and not on the raw data. This is because "the polychoric correlation, for ordered-category data, is an excellent way to measure rater agreement" Uebersax (2006). But polychoric correlation is not available in popular statistical softwares such as SPSS, SAS, Minitab, etc. Hence, we used FACTOR 9.3.1 for analyzing the raw data which provide the option of using polychoric correlations for the analysis.

The analysis was carried out basically in two broad steps. The first step involved the extraction and retention of factors and the second, rotation of the factors to simplify interpretation. Most rotation methods need the variables in the analysis to be pure measures of a single dimension if the factor solution after rotation is to be the simplest possible (Lorenzo-Seva, 2013). Thus, we would be looking out for extracted factors with the purest measures of a single dimension as possible. According to Baglin (2014), it is not important in the initial stages to indicate the number of factors to extract and retain. This is particularly important in the light of the fact that we are now exploring the "dimensionality of a scale proposing to measure a latent variable" (Baglin, 2014) and thus do not have apriori information regarding the number of factors.

This analysis utilised survey data administered to 380 students of Takoradi Polytechnic in the Western region of Ghana. However, 258 questionnaires were completed and returned representing a response rate of 68%. We computed the sample size by assuming a 95% confidence interval and 5% margin of error. The Polytechnic was then stratified into four; namely, School of Business, School of Applied Arts, School of Engineering and School of Applied Science. The respondents were then selected from each school on the basis of weights assigned relative to the total population of the Polytechnic (7780). The distributions

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were as follows: School of Business 216, School of Engineering 94, School of Applied Art 47 and School of Applied Science 23. The dataset consisted of 31 ordinal variables requiring students to indicate their level of agreement or disagreement with statements posed. The responses were analysed using FACTOR 9.3.1 (Lorenzo-Seva and Ferrando, 2015).

RESULTS

Suitability of Data

Prior to using the data for analysis, we checked to determine whether the data was suitable in the first place for EFA. To establish the suitability of the data for factor analysis, we computed univariate descriptive statistics of the 31 Likert type items of the observed data and the result presented in Table 1. Observation of Table 1 indicates that 17 of the variables exhibit kurtosis in excess of the threshold value of absolute one.

Table 1. Univariate Descriptive Statistics for the Survey Data

VAR	MEAN	CONFIDENCE INTERVAL (95%)	VARIANCE	SKEWNESS	KURTOSIS
V1	1.500	(1.41 1.59)	0.297	0.727	1.183
V2	2.367	(2.27 2.47)	0.404	1.149	0.720
V3	2.754	(2.66 2.85)	0.350	-2.032	3.228
V4	2.469	(2.26 2.68)	1.772	0.202	-1.568
V5	3.051	(2.84 3.26)	1.744	-0.216	-1.315
V6	2.590	(2.38 2.80)	0.695	0.218	-1.372
V7	2.238	(2.06 2.42)	1.307	0.689	-0.500
V8	2.543	(2.35 2.74)	1.522	0.383	-1.043
V9	2.543	(2.36 2.73)	1.334	0.437	-0.714
V10	2.453	(2.26 2.64)	1.412	0.484	-0.917
V11	2.664	(2.45 2.88)	1.739	0.278	-1.205
V12	2.578	(2.40 2.75)	1.189	0.334	-0.739
V13	2.332	(2.16 2.50)	1.112	0.548	-0.415
V14	2.383	(2.19 2.58)	1.478	0.556	-0.870
V15	2.422	(2.21 2.63)	1.752	0.489	-1.100
V16	2.527	(2.33 2.73)	1.577	0.365	-1.140
V17	3.102	(2.89 3.31)	1.763	-0.157	-1.188
V18	3.504	(3.26 3.75)	2.266	-0.546	-1.245
V19	3.461	(3.25 3.67)	1.702	-0.582	-0.884
V20	3.746	(3.54 3.95)	1.619	-0.874	-0.332
V21	3.906	(3.71 4.10)	1.452	-0.975	-0.100
V22	3.730	(3.52 3.94)	1.759	-0.857	-0.479
V23	2.594	(2.38 2.81)	1.796	0.341	-1.254
V24	3.039	(2.84 3.24)	1.561	-0.159	-1.164
V25	2.656	(2.47 2.85)	1.405	0.323	-0.934
V26	2.676	(2.48 2.87)	1.453	0.254	-1.023
V27	2.566	(2.38 2.76)	1.417	0.246	-1.110
V28	2.405	(2.20 2.61)	1.594	0.489	-1.045
V29	2.391	(2.19 2.59)	1.511	0.589	-0.835
V30	2.504	(2.31 2.70)	1.488	0.551	-0.765
V31	2.635	(2.42 2.85)	1.735	0.302	-1.196

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Also, Mardia's (1970) suggested multivariate asymmetry tests for skewness and kurtosis and the outcome is summarised in Table 2. The result shows that skewness was not statistically significant (p-value = 1.00). However, kurtosis was excessive (p-value =0.000**<0.001). As a result of the evidence adduced, we concluded that it would be inappropriate to analyse the Likert type items using familiar factor analysis (Muthén and Kaplan, 1985). In other words, parallel analysis would be used to undertake the factor analysis to avoid the limitations associated with familiar factor analysis.

Table 2. Descriptive Multivariate Asymmetry Skewness and Kurtosis of Ordinal Data

	Coefficient	Statistics	df	P
Skewness	175.365	7482.244	5456	1.0000
Skewness corrected for small sample	175.365	7575.454	5456	1.0000
Kurtosis		1079.553	10.002	0.0000**

**Significant at 0.05

Consequently, we generated a polychoric correlation matrix as advised (Muthén and Kaplan, 1985, 1992; O'Connor, 2000) and tested its adequacy. Specifically, we checked for evidence of non-zero correlations, a statistically significant Bartlett's test and a Kaiser-Meyer-Olkin (KMO) statistic above 0.80 (Beavers et al., 2013). Examination of the results showed evidence of adequacy of the polychoric correlations matrix (Determinant of Matrix = 0.000372510661760; Bartlett's statistics = 1925.1 (df = 465; p = 0.000010) and KMO test = 0.75780). This confirms the adequacy of the polychoric correlation matrix. But also, and very importantly, the polychoric correlations converged (Baglin, 2014) at a value of 0.00001 after 100 iterations contrary to some researchers (Babakus, Ferguson, and Jöreskog, 1987; Timmerman and Lorenzo-Seva, 2011) argument that polychoric correlations matrix frequently fail to converge.

Factor Extraction

Having established the suitability of the data for factor analysis we then proceeded to conduct the Parallel Analysis (PA) on the polychoric correlations matrix. However, because the study is exploratory, we used an iterative process to identify the appropriate procedure to use in determining the number of factors or components. Minimum Average Partial (MAP), Parallel Analysis (PA) (Velicer and Jackson, 1990) and Hull Method (Hull, 1965) are the procedures available in FACTOR. Based on the Unweighted Least Squares (ULS) and Minimum Rank Factor Analysis (MRFA) (Ten Berge and Kiers, 1991) factor extraction methods, we attempted to determine the number of factors to extract. However, the MAP procedure based on all the factor extraction methods under extracted the number of factors to retain (2 factors) and according to Costello and Osborne (2005) under extraction could "have deleterious effects on the results". We also avoided the use of PCA on two grounds even though it is available in FACTOR and perhaps is the most popular procedure in determining the number of factors to extract in literature. Firstly, PCA is viewed not to be a true factor analysis technique because it does not discriminate between shared and unique variance (Costello and

Osborne, 2005); secondly, findings from some studies (McArdle, 1990; Gorsuch, 1997) point to the fact that it tends to inflate values of variance accounted for by the components. Given the foregoing, we used Parallel Analysis based first on ULS and then MRFA. Both ULS and MRFA advised that six factors be extracted and retained based on the random explained common variance and optimal implementation (Timmerman and Lorenzo-Seva, 2011) of Parallel analysis for determining the number of dimensions. In determining the number of factors to retain, we used the 95th percentile criteria as it is more accurate according to results from simulation studies (Timmerman and Lorenzo-Seva, 2011). The decision for retention was derived by comparing the explained real-data eigenvalues to the 95th percentile of random eigenvalues. All variables whose real-data eigenvalues exceeded the 95th percentile of random eigenvalues where retained. Thus, on this basis six factors where retained (see Table 3). Beyond the sixth factor, the 95th percentile of random eigenvalues exceeded the real-data eigenvalue.

Table 3. Parallel Analysis Based on Minimum Rank Factor Analysis of Polychoric Correlations

Variable	Real-data eigenvalues	Mean of random eigenvalues	95 percentile of random eigenvalues
1	5.22346*	1.71793	1.82352
2	3.48343*	1.61373	1.68162
3	1.95981*	1.53803	1.59848
4	1.77396*	1.47724	1.53097
5	1.48859*	1.42046	1.47224
6	1.41702*	1.36727	1.40971
7	1.30646	1.31605	1.35767
8	1.18138	1.26953	1.31089
9	1.10507	1.22646	1.26228
10	0.96317	1.18620	1.22488
11	0.95736	1.14471	1.17968
12	0.90952	1.10522	1.13814
13	0.82868	1.06968	1.10322
14	0.77819	1.03325	1.06565
15	0.72648	0.99716	

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			1.02771
16	0.70435	0.96308	0.99480
17	0.66313	0.92874	0.95984
18	0.63107	0.89510	0.92375
19	0.57767	0.86345	0.89353
20	0.52480	0.83088	0.85890
21	0.51734	0.79898	0.82912
22	0.44838	0.76747	0.79774
23	0.41911	0.73699	0.76795
24	0.40659	0.70575	0.73491
25	0.37900	0.67546	0.70501
26	0.33594	0.64398	0.67412
27	0.32160	0.61186	0.64348
28	0.29926	0.58051	0.61320
29	0.25937	0.54523	0.57889
30	0.22727	0.50769	0.54521
31	0.18253	0.46191	0.50755

Note: The factors with asterisks are the retained factors

Factor Rotation

Now that PA has advised the number of factors to extract, we set the number of dimensions to extract manually in FACTOR to six followed by both orthogonal (varimax) and oblique (promin and promax) rotations to maximize factor simplicity and easy interpretation. But the Oblique rotation method appears more appropriate for EFA as it allows for exploration of relationships between variables in subject areas of relatively new enquiry. We rerunned the PA based on ULS and MRFA with varimax, promin and promax as the rotation methods respectively. The loadings of ULS across all the rotation methods were difficult to interpret either because of inter or intra factor cross loadings. That is, two or more items loaded on more than one factor or loaded on two or more subscales within a factor. On the basis of this, we terminated the use of ULS. With respect to MRFA, the promin rotation method showed the most promise. Notwithstanding, the loadings on the last factor (F6) were not adequate (less than 0.5). Thus, we discarded F6 and repeated the analysis but this time, manually

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setting the number of factors to extract to five based on the apriori theoretical factor structure. That is, we dropped the sixth factor before repeating the analysis. This resulted in the generation of a cleaner factor structure. However, issues of intra factor cross loadings still persisted albeit to a much lesser degree than previously; items 18, 23 and 24 did not load correctly unto their respective theoretical dimensions (see Appendix B). Consequently, we repeated the analysis once more excluding these three problematic variables mentioned earlier. All items, following the exclusion, loaded correctly onto their respective theoretical dimensions or factors with loadings of 0.5 or better (see Table 4 and Appendix A for details).

Table 4. Factor loadings, Explained Variance and Reliability of Rotated Factors

Variable	F 1	F 2	F 3	F 4	F5
V 1					
V 2					
V 3					
V 4					
V 5	0.581				
V 6	0.601				
V 7	0.513				
V 8					
V 9					
V 10					
V 11					0.576
V 12					0.710
V 13					
V 14					
V 15					
V 16					
V 17					
V 19			0.600		
V 20			0.814		
V 21			0.787		
V 22			0.731		
V 25		0.789			
V 26		0.761			
V 27		0.698			
V 28					
V 29				0.832	
V 30				0.692	
V 31					
Reliability	0.795	0.834	0.870	0.799	0.745
Variance	2.448	2.487	2.702	1.676	1.780
Proportion of Common variance	0.128	0.130	0.141	0.088	0.093

Note: Factor loadings lower than absolute 0.500 are omitted

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Overall, the explained common variance amounted to 57.94%. With respect to the individual factors, the third extracted factor (F3) accounted for the highest explained common variance of 14.1% while the fourth factor (F4) accounted for the least (8.8%). Other statistics reported include the rotated or pattern matrix, the explained variance and reliability of the rotated factors. The reliability estimates of the five extracted dimensions reflects the proportion of variability in the factor score which are explained by the latent variables. Inspection of the results in Table 4 shows that the reliability estimates of the rotated factors ranged between 0.745 and 0.870 which are reasonable.

DISCUSSION

In practice, exploratory factor analysis has been deployed in a variety of contexts including service offerings (Majors and Sedlacek, 2001), evaluation (Lovett, Zeiss, & Heinemann, 2002) and assessment (Morris, 2001). In our study, we used EFA to indentify the factors influencing the quality of students' project work in Takoradi Polytechnic; importantly from the perception of the students. Specifically, the study explored five constructs comprising of thirty one Likert type items. The constructs are the research tutor, course, facilities/resources, supervision and students. Factor analysing these items yielded five factors comprising only half of the original number of items presented to students to which they were to respond. Albeit, two of these factors (factors 4 and 5) were unstable; and according to Costello and Osborne (2005), “a factor with fewer than three items is generally weak and unstable”. There was also a reassignment of three other items from their original theoretical constructs to factors one (V23 and V24) and two (V18) of the study respectively (see Appendix B). We dealt with this problem by completely excluding them from the analysis culminating in a clean factor structure. The extracted factors related to initial constructs explored by the study. That is, the research tutor, research course, facilities /Resources, supervision and students. In general, our findings are in broad agreement with that of Isani and Virk (2005) but diverges when you narrow down to the constituent items due to the differences in the statistical treatment of the data. While Isani and Virk (2005) used descriptive statistics to derive their findings, we used EFA which is more rigorous and appropriate for the data type-ordinal data. But also observed divergence may be due to differences in contexts.

IMPLICATION TO RESEARCH AND PRACTICE

The parallel analysis approach adopted in this paper has given practical expression to one of the most controversial issues as far as factor analysis is concerned to analysing ordinal data. It should be noted that PA allowed for the conversion of the ordinal data to polychoric matrix before applying the factor analysis technique thus overcoming a weakness associated with familiar factor analysis. As a consequence, PA provides a useful shot in the arm of its proponents.

Finally, findings of this study provides an initial basis for further investigation into factors influencing the quality of students' project reports and also provides evidence for designing policies to shape the entire continuum of the research process and curriculum development involving students.

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CONCLUSION

The EFA framework used in this study is well established and extant in literature. The methodology section outlined the parallel analysis approach to EFA which has proved very useful in several contexts and practical applications. The study, adopting the parallell analysis approacvh to EFA, identified the factors which drive the quality of students' research project in Takoradi Polytechnic. Failure, in the past, to identify and address these factors has apparently caused the quality of students' research output to suffer greatly, arising mainly out of weak writing skills of students, inadequate contact hours, lack of experience on the part of supervisors among other reasons enumerated in Appendix A. These extracted items constituting the five factors in Table 4 are thus important corollary for fashioning policies for addressing issues of quality with respect to students' project works. From the findings of this study, it could be emphasised that there is strong likelihood of further deterioration of students' project reports unless adequate evidence based policy measures are implemented. However, our findings also indicate that factors four and five are weak (see Table 4) and so suggesting possible omission of some of its constituent variables. By this, we conclude that this study may not be complete and that it may be too early to conclusively say that all the potential items or variables are encapsulated in the extracted retained factors, particularly factors four and five. Perhaps, a repeat of the study with a larger dataset would be desirable.

FUTURE RESEARCH

As society become more aware, over the last decade, of the declining nature of Ghana's education generally, there is a growing chorus for practical measures to stem the trend. A fair share of these complaints have been directed at tertiary education. Indeed, a compulsory component of tertiary education is research work by students to partially fulfill conditions for graduation. But quality research by students is what is required. However, to guarantee quality students' research work, we need to identify factors that affect them which is what this study has done. In the future, a comfirmatory study will have to be done to confirm our findings using a much larger sample (1000 or more). But, also, we need to explore the relationship between these factors through evidence from students, academics and other non-teaching staff of the polytechnic so that measures taken would be appropriate and optimal.

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APPENDIX A

FACTOR 1 (STUDENT)	LOADINGS
V5 Attitude of students towards research and project work is very poor	0.581
V6 The project research background of students is weak	0.601
V7 Polytechnic students perceive project/research work as irrelevant	0.513

FACTOR 2 (SUPERVISOR)	LOADINGS
V25 Attitude of students towards research and project works is very poor	0.789
V26 The project research background of students is weak	0.761
V27 Polytechnic students perceive project/research works as irrelevant to their study although it is a requirement for graduation	0.698

FACTOR 3 (RESEARCH COURSE)	LOADINGS
V19 Supervisors do not make enough time for their research students	0.600
V20 Supervisors lack the relevant experience in the area of research themselves	0.814
V21 Most supervisors are not given proper training or refresher courses for quality supervision	0.787
V22 Inadequate and proper coaching at each research stage is not duly offered by supervisors	0.731

FACTOR 4 (STUDENT)	LOADINGS
V29 The academic writing skills of students are very weak	0.832
V30 Student workload and credit required is too much to allow for quality work to be done	0.692

FACTOR 5 (TEACHING)	LOADINGS
V11 The manner in which research is taught makes it difficult for students to prepare their synopsis	0.576
V12 The duration for teaching research methods is highly inadequate	0.710

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Appendix B. Factor loadings, Explained Variance and Reliability of Rotated Factors

Variable	F 1	F 2	F 3	F 4	F5
V 1					
V 2					
V 3					
V 4					
V 5			0.569		
V 6			0.634		
V 7			0.545		
V 8					
V 9					
V 10					
V 11					0.579
V 12					0.653
V 13					
V 14					
V 15					
V 16					
V 17					
V 18		0.755			
V 19		0.647			
V 20		0.811			
V 21		0.765			
V 22		0.665			
V 23	0.690				
V 24	0.740				
V 25	0.757				
V 26	0.809				
V 27	0.585				
V 28					
V 29				0.788	
V 30				0.747	
V 31					
Reliability	0.878	0.887	0.806	0.796	0.754
Variance	3.286	3.242	2.522	1.673	1.968
Proportion of Common variance	0.148	0.146	0.114	0.076	0.089

Note: Factor loadings lower than absolute 0.500 are omitted

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