Journal of Anxiety & Depression

Research | Vol 5 Iss 2
ISSN: 2582-3264
https://dx.doi.org/10.46527/2582-3264.151

Effects of Education and Occupation on the JMLQ Aptitude Test

Bengt Jansson[1,2], Rose Mary Erixon[2] and Trevor Archer[1*]

[1]JobMatch Talent, Skårsled, Almedal, Gothenburg, Sweden

[2]Department of Psychology, University of Gothenburg, Gothenburg, Sweden

[*]**Corresponding author:** Archer T, JobMatch Talent, Skårsled, Almedal, Gothenburg, Sweden, Tel: + 46 31-33 55 940; E-mail: trevorcsarcher49@gmail.com

Received: November 28, 2022; **Accepted:** December 14, 2022; **Published:** December 23, 2022

Abstract

The participants were recruited from the social media platforms and presented a mean age of 45 years, with a SD of 12.6, and therewith reported their corresponding educational levels and essential occupational orientations; they were subjected accordingly to the JMLQ adaptive, recruitment test instrument. Analysis of their responses indicated that the participants' performances were subject to the influence of level of education and occupational complexity/specialization such that the highest levels of education and occupational complexity were reflected, firstly, at the highest Basic JMLQ scales, consisting of Complex, Mathematical, Numerical, and Logical, mean values, and secondly, the highest levels of proportion correct answers performance was obtained at five years university or more compared to post-secondary education which was higher than upper secondary school, and finally thirdly, the high category of occupation, i.e. most specialized, based upon hypothesized JMLQ score produced the highest mean values for General, Speed and Speed2 categories followed by the medium and low categories, respectively. In consensus, the present findings have implied that the highest academic levels and greatest level of occupational specializations produced the paramount performance of logical reasoning and cognitive finesse. Accordingly, the JMLQ instrument apportions sophistication and suitability for both the applications and conceptualizations of logical-cognitive reasoning and/or intellectual performance assessment.

Keywords: *Aptitude; Education; Occupation; Performance; Correlation; Reasoning; Cognition; JMLQ instrument*

1. Introduction

The performance of reasoning and logical aptitude testing appears to be affected, to greater or lesser extents, by the direct and/or indirect relationships between word-problem solving, logical reasoning, inference making, and reading comprehension-linguistic skills. Fundamental to its endeavors, the processing of rational reasoning within cognitive tasks of complex demands is required. In this context, the responses of "high-capacity", as opposed to "low-capacity", reasoners, applying the accuracy-capacity relationship observed in reasoning occurring as a consequence of the "intuitive" or "Type I" processing propensity, is

Citation: Jansson B, Erixon RM, Archer T. Effects of Education and Occupation on the JMLQ Aptitude Test. J Anxiety Depress. 2022;5(2):151.

expected to produce both higher levels of accuracy combined with a greater rate-of-processing (more speed) in cognitive performances thereby presupposing the 'deepest' or semantic levels of information processing. Both construct and discrimination validity are necessary determinants of the eventual utility of instruments applied in psychometric research, particularly with regard to logic and reasoning ability [1]. Much effort has been invested in devising methods aimed at the correction of statistical artifacts, such as sampling error, unreliability of measuring instruments, and restriction of range, and integrating these studies into meta-analyses [2,3] wherein the corrections, between IQ tests and job performance, originally low, doubled the correlations to approximately 0.5. Nevertheless, the consensus from correlational analyses between job performance and IQ-levels remains difficult to interpret [4]; the present analysis attempts to elucidate this issue through application of a newly developed instrument.

The term, 'intelligence', provides one of several expressions for describing individuals' differences in thinking and reasoning skills, that include cognitive ability, cognitive performance, cognitive functioning, mental ability, etc. The intelligence or reasoning developmental period from late childhood to adolescence to young adulthood comprised a behavioral metamorphosis involving executive control and emotional regulation, on the one hand, and universal-differential aspects of cognition, on the other [5]. Universal changes involve (i) competencies, expressed through 'deductive reasoning' [6], (ii) hypothesis testing by 'control-of-variable strategies' [7], and 'proportional reasoning' [8]. In a study involving N1=251, N2=566 fourth- and fifth-graders, respectively, Thurn et al., [9] observed that mathematical achievement and prior knowledge mediated the relation between intelligence and proportional reasoning and thereby enabling these pupils to exploit their learning opportunities in more sophisticated manners. In this regard, it ought to be recognized that the predictive model, formed by reasoning, verbal fluency, executive functions, and, not least, self-esteem, explained 55.4% of the academic performances [10]. Higher levels of education contribute to occupational achievement whereby parental socioeconomic status were associated with intelligence and cognitive ability [11]; within the different components of cognition, verbal ability produced the highest levels of occupational success. About one hundred years ago, Kornhauser [12] demonstrated that the higher the level of occupational sophistication/finesse, the higher the level of intelligence scoring.

Nevertheless, neither that initial insight nor subsequent treatises have shown that high intelligence scoring, linked with higher occupational status and education, is associated also with a higher rate of responding (i.e., speed in answering).

It was observed previously that the correlations between incidence of "Correct answers" and the "Time-taken to answer" were, largely, both high and negatively related (i.e., - 0.60 to - 0.89), which promoted the implication that the "correct answers" related strongly with the shorter intervals within the "time to answer" (or rate of responding) [13,14]. In the Jansson et al. [14] study two different types of cognitive/logical processing were distinguished: (a) an 'experiential' process, that involved the Complex and Mathematical skills of each individual; and (b) the 'intuitive' process, that involved the Logical and Speed skills of each individual, respectively, whereas numerical skills were interpreted as invoking an 'intuitive processing within framed experience'. Through the expediency of relating features of a psychometric inventory to pre-existing phenomena, such as educational and occupational agencies, an indication of its predictive efficacy was foreseen. Apropos of aptitude testing, the higher requirements for a task of logical and cognitive abilities, the higher test scores would be expected for appropriateness and fitness of the instrument [15]. The purpose of the present study was to analyze the effects of educational and occupational agencies on performance of the JMLQ test scores.

2. Methods and Materials

2.1 Participants

The participants for this study were recruited from dual social media platforms (LinkedIn, Facebook), wherein they reported their level of educational level and fundamental occupational-work orientation. The number of participants accounted for in the preliminary sections initially numbered 1028 individuals. Nevertheless, in attempts to establish normal frequency distributions of the obtained IQ scores in lieu of extreme values by removal of outliers, sample sizes for the General and Traits scales varied from 990 to 1017 participating subjects.

Thus, the final results of this study were based upon a population of 1017 participants, of whom 742 were female (73.1%), and 259 were male (25.5%) participants, and 16 participants expressed other genders (1.5%). The age range varied from 18 to 81 years (M=45, SD=12.6), women (M=46, SD=11.6), men (M=41, SD=14.4) and others (M=41 years, SD=14.1).

2.2 Instruments

The JMLQ adaptive recruitment test consisted of four "Basic" scales: (a) Complex Cognition: The individual's ability to comprehend complex ideas and information; (b) Mathematical understanding: The person´s general understanding of mathematics principles; (c) Numeric understanding: The person´s general understanding of numbers based on basic arithmetical competence; (d) Logical reasoning: The person's ability to draw inference-based conclusions.

Furthermore, the JMLQ instrument included three additional scales: (i) General factor: A scale constructed to be an average of the four Basic scales (above); (ii) Speed: The cognitive processing speed in which the person may comprehend and react to the presented information; (iii) Speed2: A scale that differs from Speed through applying a mixture of numerical and spatial items (whereas the Speed scale only consisted of spatial items).

2.3 Design

The thirteen occupations were each in turn categorized into ordinal levels (low, medium, high) based on expected requirements for the logical and cognitive abilities. Categories with relatively low anticipated requirements were Care, Manual work, Service/support, All-round. On the other hand, Specialist, IT/Technics were associated with high anticipated requirements for logical and cognitive abilities [14,16].

See TABLE 2 - 1 below (in Results) for a detailed description of the Occupational levels (low, medium, high). For Education, three ordinal levels were used (upper secondary school; post-secondary education; university, 5 years or more).

2.4 Statistical procedure

In order to discover linear trends, line graphs of JMLQ test scores over the ordinal levels for Education and Occupations were used. In addition, the four Basic scales were compared using ANOVA with repeated measures. Specifically, based on the line graphs, Complex/Math and Logic/Numeric were pairwise aggregated, respectively, in the ANOVAs. It should be noted that analyses were performed with SPSS (ver. 26).

3. Results

Conjointly, 62 cases were excluded from analyses due to an unaccountably low level of responding to the JMLQ items by these participants. Thus, sample sizes for Education were N=955 individuals eventually, whereas N=469 individuals represented the level of responding applied to Occupation. Frequencies for the occupational levels varied approximately between 60 and 260 (see TABLE 1, below).

TABLE 1. **Frequencies of reported Occupations (during the last five years) across Hypothesized categorizations (low, medium, high) of correct answering (N = 469).**

		Hypothesized JMLQ score			
		Low	Medium	High	
Occupations During the last 5 years					
	Care	84			
	Manual work	30			
	Service/support	17			
	All-round	16			
	Consultation		76		
	Administration		66		
	Leadership		56		
	Sales		23		
	Com & info		17		
	Design, creation		16		
	Security		6		
	Specialist			32	
	IT/Technics			30	
Total N:		147	260	62	= 469

Com: communication; Info: information; IT: information technology

Among all of the line graphs shown below, the Basic scales (Complex, Math, Numeric, Logic) were separated from the Additional scales (General, Speed 1&2). For the "Basic" scales, on both educational and occupational levels, similar patterns appeared with upward trends. Means of 'Proportion correct', followed an order (from low to high) according to Complex, Math, Logic, and Numeric.

In the line graphs shown below, there was an interaction effect between both pairs of "Basic" scales ('CoMa' vs 'LoNu'): a 'jerk or sharp movement' occurs for Complex and Math at the high level for both Education and Occupation (cf. 'experiential' scales from Table 3). For a detailed overview, see FIG. 1 & 2.

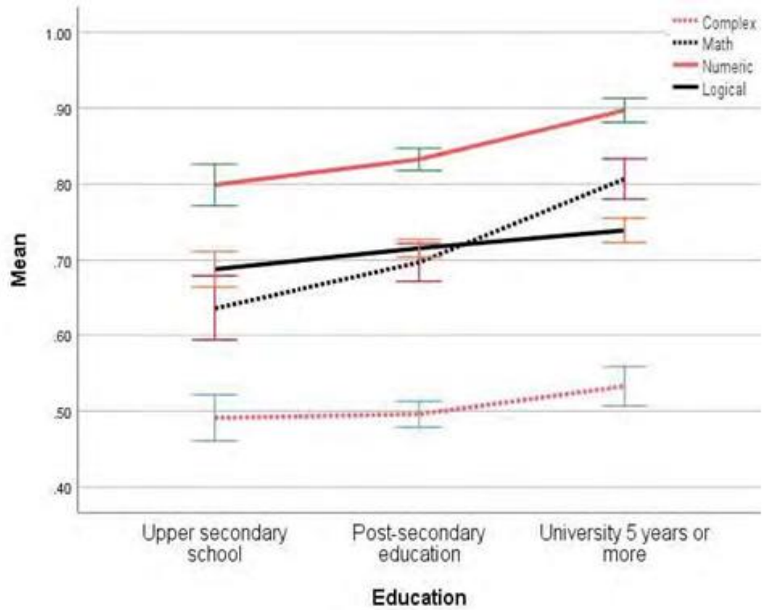

FIG. 1. **Mean values pertaining to the correct answers from the "Basic" JMLQ scales (Complex, Math, Logic, Numeric) over Education levels, wherein N=955).**

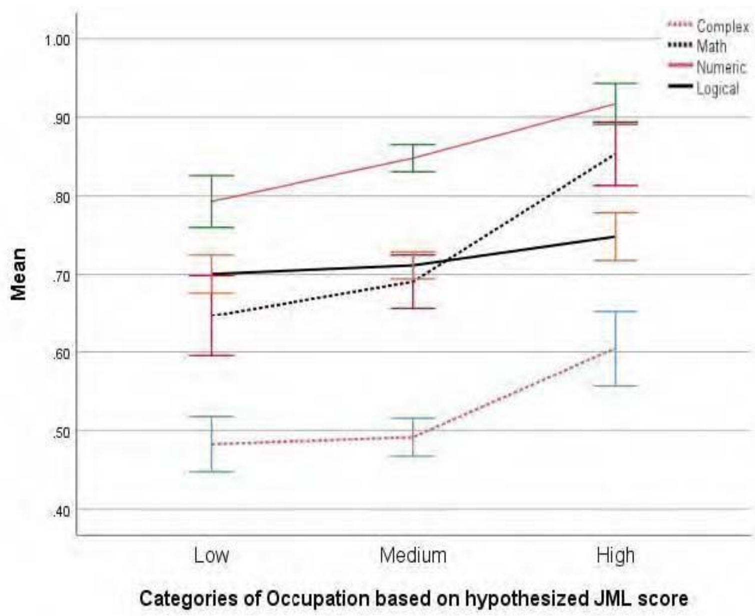

FIG. 2. **Mean values of correct answers of Basic JMLQ scales (Complex, Math, Logic, Numeric) over hypothesize Occupational categorizations (N=469).**

The line graphs above were compared analytically using two ANOVAs with repeated measures. There was a significant interaction effect between 'CoMa*LoNu' for both Education and Occupation. The corresponding effects sizes were 0.089 and 0.061, respectively). Thus, the 'CoMa' line with a 'jerk', and the linear 'LoNu' line were invariant over Education and Occupation. In addition, there were significant main effects of each, as well as interaction effects between Education and Occupation, respectively. See TABLES 2 & 3, below.

TABLE 2. **ANOVA with repeated measures of correct answers for paired Basic JML scales (CoMa [Complex, Math] vs LoNu [Numeric, Logic]) over the three Educational levels N=955).**

Tests of Within-Subjects Effects

	Type III Sum Of Squares	df	Mean Square	F	Sig.	Partial Eta Squared Source
CoMa	22.609	1	22.609	1389.818	.000	.601
CoMa*EDUC	.159	2	.079	4.881	.008	.010
Error(CoMa)	15.015	923	.016			
LoNu	22.387	1	22.387	816.694	.000	.469
LoNu*EDUC	.905	2	.453	16.512	.000	.035
Error(LoNu)	25.301	923	.027			
CoMa*LoNu	1.224	1	1.224	90.331	.000	.089
CoMa*LoNu*EDUC	.181	2	.091	6.686	.001	.014
Error*(CoMa*LoNu)	12.505	923	.014			

Tests of Between-Subjects Effects

	Type III Sum Of Squares	df	Mean Square	F	Sig.	Partial Eta Squared Source
Intercept	1534.619	1	1534.619	15329.04	.000	.943
EDUC	3.811	2	1.905	19.033	.000	.040
Error	92.403	923	.100			

TABLE 3. **ANOVA with repeated measures of correct answers for paired Basic JML scales (CoMa [Complex, Math] vs LoNu [Numeric, Logic]) over the hypothesized Occupational categorizations (N=469).**

Tests of Within-Subjects Effects

	Type III Sum Of Squares	df	Mean Square	F	Sig.	Partial Eta Squared Source
CoMa	8.374	1	8.374	479.574	.000	.507
CoMa*hypo_OCC	.379	2	.189	10.848	.000	.044
Error(CoMa)	8.137	466	.017			
LoNu	9.352	1	9.352	314.344	.000	.403
LoNu*hypo_OCC	.319	2	.160	5.368	.005	.023

Error(LoNu)	13.865	466	.030			
CoMa*LoNu	.436	1	.436	30.276	.000	.061
CoMa*LoNu*,						
Hypo_OCC	.004	2	.002	.131	.877	.001
Error*(CoMa*LoNu)	6.714	466	.014			

Tests of Between-Subjects Effects

	Type III Sum Of Squares	df	Mean Square	F	Sig.	Partial Eta Squared Source
Intercept	671.929	1	671.929	6909.706	.000	.937
Hypo_OCC	2.666	2	1.333	13.706	.000	.056
Error	45.316	466	.097			

The final two-line graphs consisted of the relatively invariant patterns for the Additional scales (General, Speed 1&2) over Education and Occupation. This pattern appeared, from the bottom up, with respect to means for Proportion correct. For Occupation, the General scale had an upward jerk at the highest level. This effect may be an effect due to the “Basic” scales that were included in the General scale. See for further information Figures 3 & 4, below.

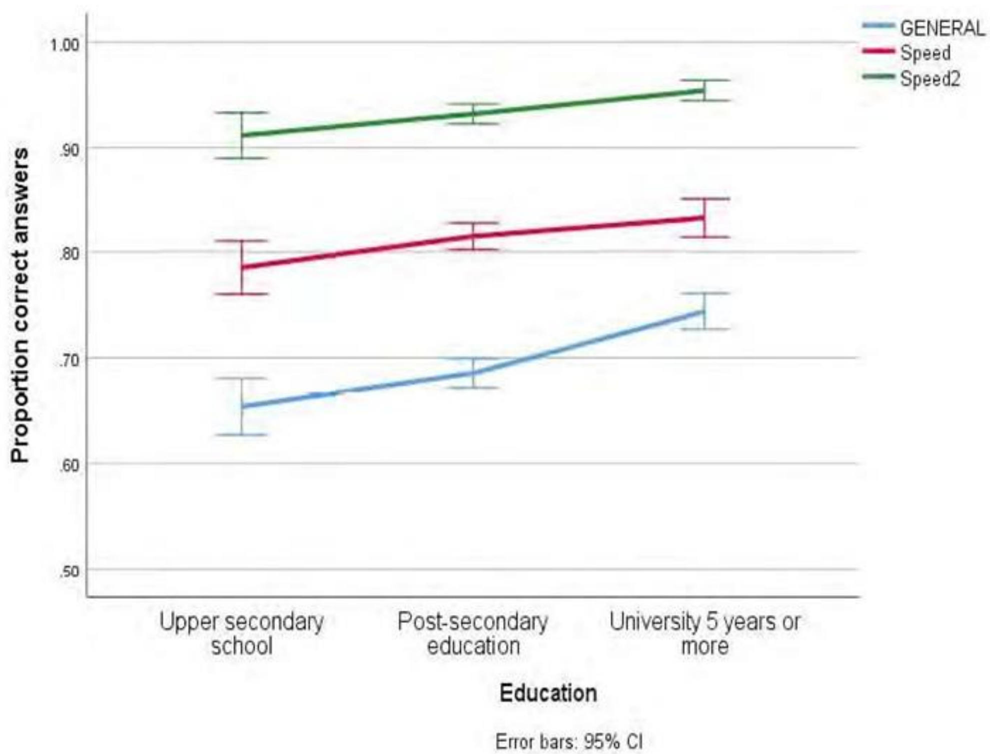

FIG. 3. **Mean values of correct answers of Additional JMLQ scales (General, Speed 1&2) over Education levels N=955).**

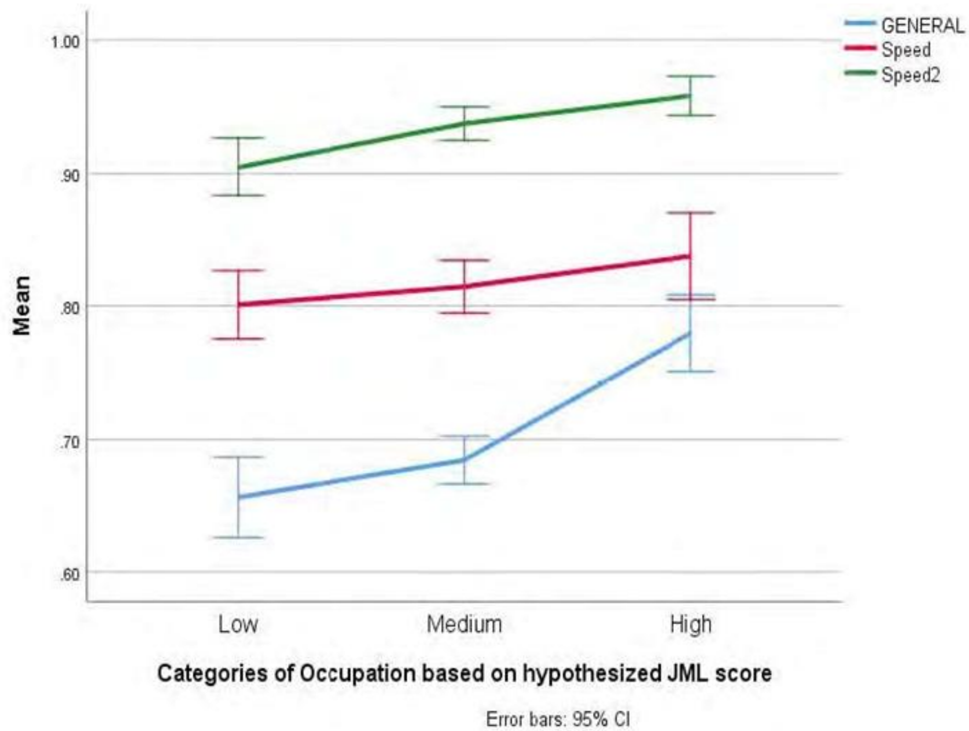

FIG. 4. **Mean values of correct answers of Additional JML scales (General, Speed 1&2) over hypothesize Occupational categorizations (N=469).**

4. Discussion

The findings of the present study, pertaining the influence of level of education and occupational complexity/specialization, may be summarized according to the following observations: (i) the highest levels of education and occupational complexity were mirrored in the highest "Basic" JMLQ scales, consisting of the Complex, Mathematical, Numerical, and Logical mean values obtained, and (ii) the highest levels of 'proportion of correct answers' performance were obtained at five years of university education or more compared to post-secondary level of education which was higher, respectively, than upper secondary school level, and, finally, (iii) the highest category of occupation based upon the hypothesized JMLQ score displayed the highest mean values for General, Speed and Speed2 categories followed by the medium and low categories of occupational specialization, respectively. Thus, it is established that the highest academic levels and greatest occupational specializations produced the paramount performance of logical reasoning and cognitive finesse.

General intelligence (g) which may be construed also as a statistical phenomenon and reasoning ability may affirm a global finding, as derived from the different batteries of cognitive tests that encompass intelligence parameters, such as general intelligence performance, cognitive domains and individual cognitive tests [17]. Intelligence measures are advanced as among the most reliable, consistent, and valid predictors of high-level job performance, learning both suitably and competently on the job, and the job performance developmental trajectory, with moderately adjusted correlations [18] over a spectrum of gradings pertaining to job-complexity. Measurable expressions of intelligence, as operationalized through cognitive test scores, show robustly characterized phenotypic formulations, reliably high test-retest stability, and certain predictive validity for educational levels, work and occupation, and health parameters [19]; all of these observations make contributions to the broader construct validity, particularly in the context of “rate-of-responding” [20,21]. In efforts to derive the environmental, social, and genetic background of intelligence expression from an epigenetic perspective, Deary et al. [22] have examined (i) molecular genetic (DNA-based data) findings upon intelligence parameters, (ii) the genetic loci corresponding to reasoning, cognition and intelligence performance, (iii) DNA-based heritability analyses concurrent with intelligence, and, lastly, (iv) the genetic relationships corresponding to intelligence measures in connection with other phenotypic traits based upon novel brain imaging-intelligence observations that include whole-brain concomitants together with grey and white matter regional characterisations [23].

Taking into consideration the consensus from correlational analyses between job performance and IQ-levels, certain conclusions regarding correct responding and/or “rate-of-responding” in comparisons of ‘test validity’ that have been expressed remain difficult to interpret [4]. Nevertheless, the present findings, that replicate once again the associations between high performance and speed of responding [14], give strong credence to the postulate that higher levels of logical reasoning and/or cognitive performance are related to higher hypothesized levels of occupational performance. Taken together, the consensus appears to be that the JMLQ instrument presents valid and reliable psychometric properties, as well as providing a useful tool to assess professional competencies in occupational situations wherein individuals, on the basis of educational proficiency may be predicted to offer a performance qualification. The relationships between job performance and educational level and reasoning/cognitive capability have been the focus of several research incitements [24]. Information concerning individuals’ occupational skillfulness and completed years of education affects estimated global intelligence and obtained IQ scores [25], with Intelligence test scores displaying the well-documented predictability of level of educational and occupational achievement/sophistication established over worldwide confirmation [26,27]. Additionally, high levels of correlation coefficients (between 0.5 to 0.6) between educational achievement parameters, i.e., education level/school grades and intelligence scoring were obtained in longitudinal studies [28,29]. Finally, unsuccessful educational and occupational achievements, among an exceedingly large population of Danish individuals (N=1,098,742 aged 18 years, Copenhagen), obtained from a draft board over the course of intervals from 1968 to 1984 and from the intervals from 1987 to 2015, was found to be a powerful and constant predictor of low IQ levels [30].

5. Conclusions

The present study demonstrates the postulated relationship between the highest levels of education and specialization of occupation for the highest performances on the JMLQ instrument for logical reasoning and cognition. It confirms the reliability and validity several accounts of the influence of these aspects (i.e., education and occupation) pertaining to performance and “rate-of-responding”, both as a valid construct and a developmental index. Thus, correct performance and “rate-of responding” in IQ tests bear direct relationships to both high education level and job-finesse, on one hand, and low education level and job-ineptness, on the other.

6. Limitations

An obvious limitation of the present study was the lack of any other demographic features, besides age, educational level and occupational specialization, such as health and personality characteristics, that have affected attitudes towards the JMLQ instrument. Nevertheless, since the methodological features of this study were the main focus, it was considered that only those demographics included were of relevance.

7. Acknowledgement

The authors acknowledge the expertise provided by Klaus Olsen. This research was supported by a grant from JobMatchTalent.

8. Contributors

All contributed equally to this manuscript and approved the final version of the article.

9. Conflict of Interest

The authors declare no conflict of interest. The authors were given complete autonomy of planning, design, procedure and conclusions.

REFERENCES

1. Bhat MA. Construction and evaluation of reliability and validity of reasoning ability test. Int J Educ Stud. 2014;01(02):47-52.
2. Schmidt FL, Hunter JE. History, development, evolution, and impact of validity generalization and meta-analysis methods. In: Murphy KR, editor. Validity generalization: A critical review. Hove: Erlbaum, England; 2003. 1975-2001 p.
3. Wiernik BM, Dahlke JA. Obtaining unbiased results in meta-analysis: The importance of correcting for statistical artifacts. Association for Psychological Science. 2020;3(1):94-123.
4. Richardson K, Norgate SH. Does IQ really predict job performance. Appl Develop Sci. 2015;19(3):153-69.
5. Demetriou A, Gustafsson JE, Efklides A, et al. Structural systems in developing cognition, science, and education. Neo-Piagetian Theories of Cognitive Development. In: Demetriou A, Shayer M, Efklides A, editors. London and New York: Routledge; 2002. 79-103 p.
6. Halford Graeme S, Andrews G. The development of deductive reasoning: How important is complexity? Think Reason. 2004;10(2):123-45.
7. Martin S, Croker S, Zimmerman C, et al. Teaching the control-of-variables strategy: A meta-analysis. Developmental Review. 2016;39:37-63.
8. Francoise T, Pulos S. Proportional reasoning: A review of the literature. Educ Stud Math. 1985;16(2):181-204.
9. Thurn C, Nussbaumer D, Schumacher R, et al. The Role of Prior Knowledge and Intelligence in Gaining from a Training on Proportional Reasoning. J Intell. 2022;10(2):31.
10. Quílez-Robres A, Moyano N, Cortés-Pascual A. Executive Functions and Self-Esteem in Academic Performance: A Mediational Analysis. Int J Psychol Res (Medellin). 2021;14(2):52-60.
11. Anni K, Mõttus R. Intelligence as a predictor of social mobility in Estonia. Scand J Psychol. 2019;60(3):195-202.
12. Kornhauser AW. Intelligence Test Ratings of Occupational Groups. The American Economic Review. 1925;15(1):110-22. Supplement, Papers and Proceedings of the Thirty-seventh Annual Meeting (Mar, 1925).
13. Archer T, Jansson B, Olsen K, et al. Cognitive Performance as a Function of Job Match Logic Aptitude Test. In J Sch Cogn Psychol. 2021;10.35248/2329-8901.19.8.215.
14. Jansson B, Olsen K, Erixon RM, et al. Cognitive performance as a function of jobmatch logic aptitude test: Individual differences associated with response time. In J Sch Cogn Psychol. 2021;2(1):115.

15. Khaligh-Razavi SM, Habibi S, Sadeghi M, et al. Integrated Cognitive Assessment: Speed and Accuracy of Visual Processing as a Reliable Proxy to Cognitive Performance. Sci Rep. 2019;9(1):1102.
16. Jansson B, Erixon RM, Archer T. Investigating Mental Health Status in High School Students. J Anxiety Depress. 2021;5(2):147.
17. Deary IJ. The stability of intelligence from childhood to old age. Curr Dir Psychol Sci. 2007;23(4):239-45.
18. Schmidt FL, Hunter JE. General mental ability in the world of work: Occupational attainment and job performance. J Pers Soc Psychol. 2004;86(1):162-73.
19. Der G, Deary IJ. The relationship between intelligence and reaction time varies with age: Results from three representative narrow-age age cohorts at 30, 50 and 69 years. Intelligence. 2017;64:89-97.
20. Deary IJ, Johnson W, Starr JM. Are processing speed tasks biomarkers of cognitive aging? Psychol Aging. 2010;25(1):219-28.
21. Deary IJ, Penke L, Johnson W. The neuroscience of human intelligence differences. Nat Rev Neurosci. 2010;11(3):201-11.
22. Deary IJ, Cox SR, Hill WD. Genetic variation, brain, and intelligence differences. Mol Psychiatry. 2022;27(1):335-53.
23. Hilger K, Winter NR, Leenings R, et al. Predicting intelligence from brain gray matter volume. Brain Struct Funct. 2020;225(7):2111-29.
24. Martinez-Matute M, Villaneuva E. Task specialization and cognitive skills: evidence from PIAAC and IALS. Rev Econ Household. 2021:10.1007/s11150-021-09587-2.
25. Leli DA, Filskov SB. Relationship of intelligence to education and occupation as signs of intellectual deterioration. J Consult Clin Psychol. 1979;47(4):702-07.
26. Gottfredson LS. g, jobs and life. Chapter 15. In: Nyborg H, editor. The Scientific Study of General Intelligence. Oxford: Pergamon, UK; 2003. 293-342 p.
27. Strenze T. Intelligence and socioeconomic success: A meta-analytic review of longitudinal research. Intelligence. 2007;35:401-26.
28. Deary IJ, Johnson W. Intelligence and education: causal perceptions drive analytic processes and therefore conclusions. Int J Epidemiol. 2010;39(5):1362-69.
29. Roth B, Becker N, Romeyke S, et al. Intelligence and School grades: a Meta-analysis. Intelligence. 2015;53:118-37.
30. Hegelund ER, Flensborg-Madsen T, Dammeyer J, et al. Low IQ as a predictor of unsuccessful educational and occupational achievement: A register-based study of 1,098,742 men in Denmark 1968-2016. Intelligence. 2018;71:46-53.