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# Effects of Education and Occupation on the JMLQ Aptitude Test

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## Abstract

Participants, recruited from social media platforms with mean age of 65 years (SD = 12,6), and reporting their respective educational levels and primary occupational orientations were subjected to the JMLQ adaptive test instrument. It was observed from the participants' performance that the influence of level of education and occupational complexity/specialization induced logical capacity features indicating that the highest levels of education and occupational complexity were reflected at the highest Basic JMLQ scales, consisting of Complex, Mathematical, Numerical, and Logical, mean values, 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, these findings have implied that the highest academic levels and greatest level of occupational specializations produced the paramount performance of logical reasoning and cognitive finesse, and thus JMLQ instrument ought to offer a high degree of suitability for both applications and conceptualizations of logical-cognitive reasoning assessment.

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## 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 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. [15](2021) study two different types of cognitive/logical processing were distinguished: (a) an 'experiential'

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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 [16]. The purpose of the present study was to analyze effects of educational and occupational agencies on performance of the JMLQ test scores.

## Methods and Materials

### Participants

Participants were recruited from two social media platforms (LinkedIn, Facebook), participants reported their educational level and primary occupational orientation.

The number of participants accounted for in the preliminary sections were initially 1028. However, in order to develop normal frequency distributions of IQ scores without extreme values by removal of outliers, sample sizes for the General and Traits scales varied between 990 to 1017 subjects. The results of the study were based on 1017 participants, 742 women (73.1%), 259 men (25.5 %) and 16 other (1.5 %). The age range was 18 – 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).

### Instruments

The JMLQ adaptive test included four Basic scales: (a) Complex Cognition: The person's ability to understand 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 arithmetic's; (d) Logical reasoning: The person's ability to make inference-based conclusions.

Moreover, the JMLQ included three Additional scales: (i) General factor: A scale created as an average of the four Basic scales (above); (ii) Speed: The cognitive processing speed in which the person can understand and react to information; (iii) Speed2: A scale that differs from Speed by having a mix of Numerical and spatial items (whereas Speed only consists of spatial items).

### Design

Thirteen occupations were categorized into ordinal levels (low, medium, high) based on expected requirements for 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 [14,15]. 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).

### 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).

## Results

Taken together, 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 = 926-eventually, whereas N = 469 was the level of responding applied to Occupation. Frequencies for occupational levels varied approximately between 60 and 260 (Table 1).

| | Hypothesized JML score | | |
|---|---|---|---|
| Occupations the last 5 years | Low | Medium | High |
| Care | 84 | | |
| Manual work | 30 | | |
| Service/support | 17 | | |
| All-round | 16 | | |
| Consultation | | 76 | |
| Administration | | 66 | |
| Leadership | | 56 | |
| Sales | | 23 | |
| Com & info | | 17 | |
| Design, creativity | | 16 | |
| Security | | 6 | |
| Specialist | | | 32 |
| IT/Technics | | | 30 |
| Total | 147 | 260 | 64 |

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

In all the line graphs 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 graphsbelow, there was an interaction effect between both pairs' 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, (Figures 1 & 2).

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 (Tables 2 & 3).

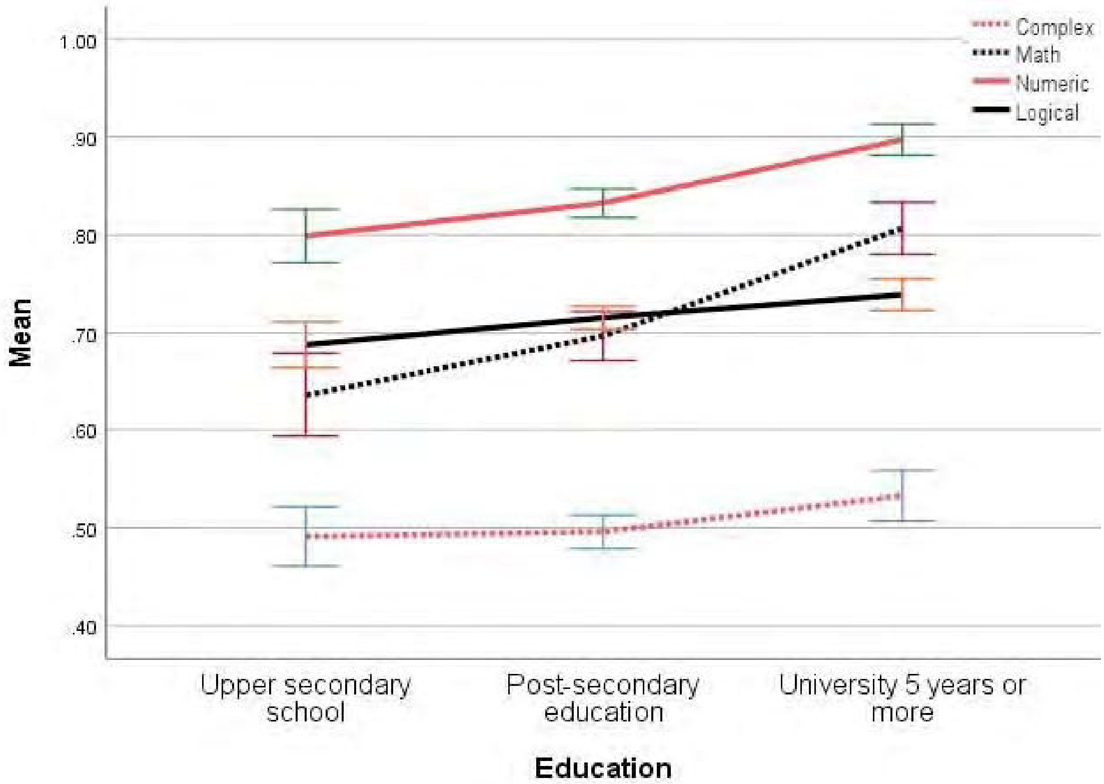


Figure 1: Mean values of correct answers of Basic JML scales (Complex, Math, Logic, Numeric) over Education levels N = 955).

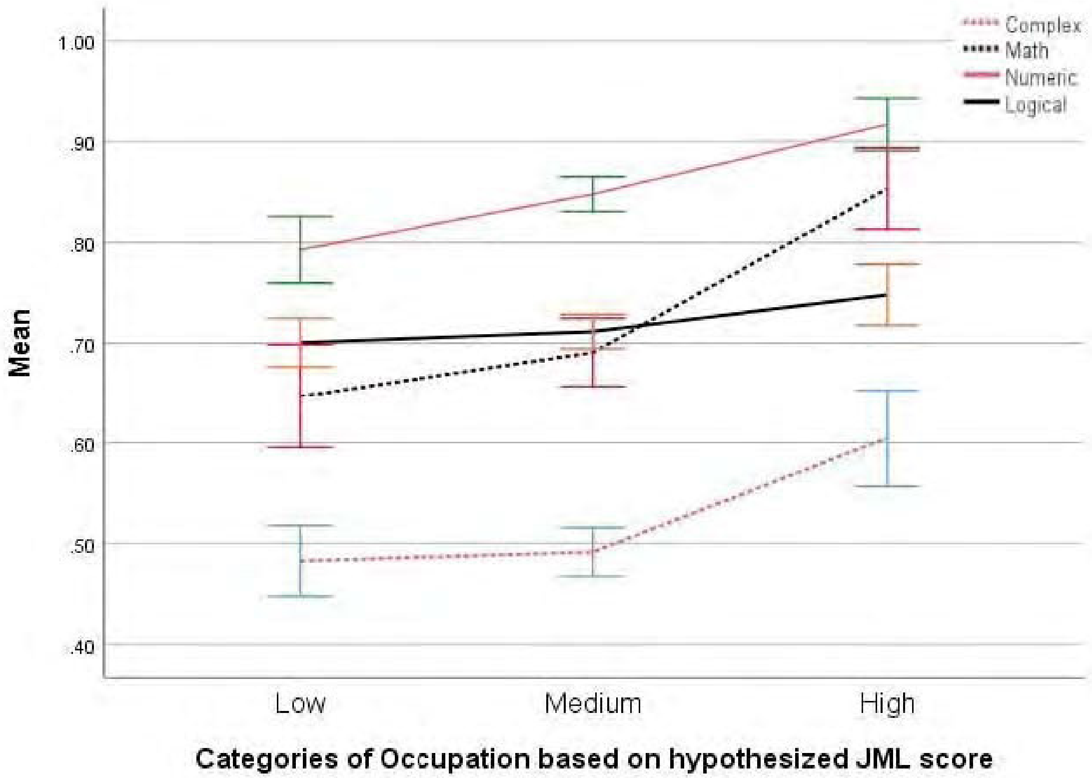


Figure 2: Mean values of correct answers of Basic JML scales (Complex, Math, Logic, Numeric) over hypothesize Occupational categorizations (N = 469).

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Tests of Within-Subjects Effects

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|
| 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 | 90.331 | .001 | .014 |
| Error*(CoMa*LoNu) | 12.505 | 923 | .014 | | | |
| 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 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).

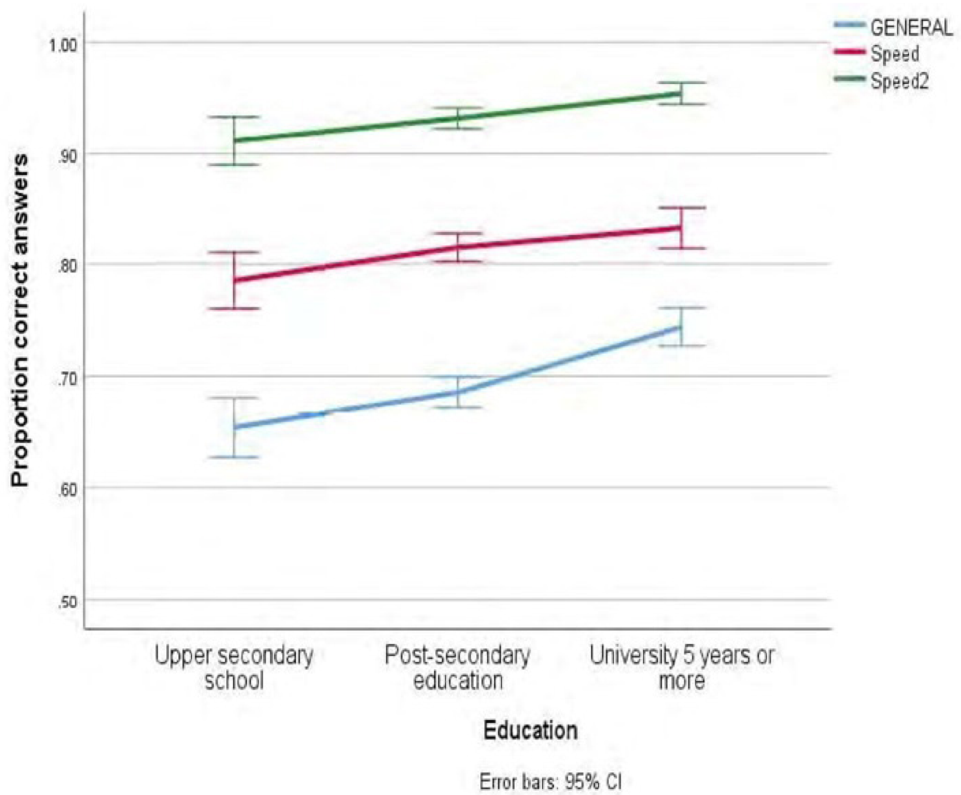


Figure 3: Mean values of correct answers of Additional JML scales (General, Speed 1&2) over Education levels N = 955).

## Discussion

The findings of the present study, pertaining the influence of level of education and occupational complexity/specialization, indicated the following observations: (i) the highest levels of education and occupational complexity were mirrored in the highest Basic JML scales, consisting of Complex, Mathematical, Numerical, and Logical, mean values, and (ii) 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 (iii) the high category of occupation based upon hypothesized JML score produced the highest mean values for General, Speed and Speed2 categories followed by the medium and low categories, respectively. Thus, it is established that the highest academic levels and greatest occupational specializations produced the paramount performance of logical reasoning and cognitive finesse.

Tests of Within-Subjects Effects

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|
| CoMa | 8.374 | 1 | 8.374 | 479.574 | .000 | .507 |
| CoMa*hypo_OCC | .379 | 2 | .079 | 10.848 | .000 | .044 |
| Error(CoMa) | 8.137 | 466 | .016 | | | |
| LoNu | 9.352 | 1 | 22.387 | 314.344 | .000 | .403 |
| LoNu*hypo_OCC | .319 | 2 | .453 | 5.368 | .005 | .023 |
| Error(LoNu) | 13.865 | 466 | .027 | | | |
| CoMa*LoNu | .436 | 1 | 1.224 | 30.276 | .000 | .061 |
| CoMa*LoNu*, | | | | | | |
| Hypo_OCC | .004 | 2 | .014 | .131 | .877 | .001 |
| Error*(CoMa*LoNu) | 6.714 | 466 | 1534.619 | 6909.706 | | |
| Intercept | 671.929 | 1 | 1.905 | 13.706 | .000 | .937 |
| Hypo_OCC | 2.666 | 2 | .100 | | .000 | .056 |
| Error | 45.316 | 466 | | | | |

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

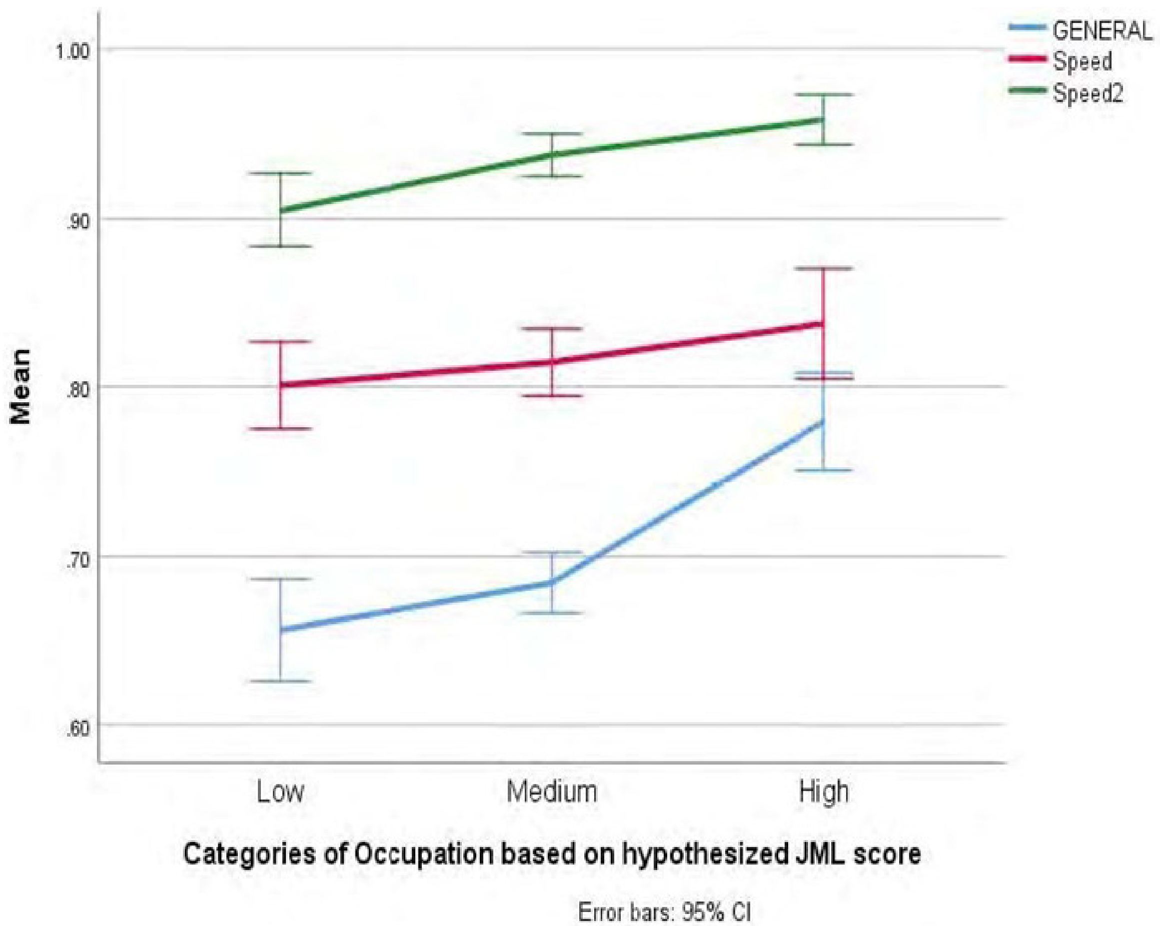


Figure 4: Mean values of correct answers of Additional JML scales (General, Speed 1&2) over hypothesize Occupational categorizations (N = 469).

General intelligence (g), viewed as a statistical phenomenon, presents a universal finding as derived from different batteries of cognitive tests that encompass levels such as general intelligence, cognitive domains and individual cognitive tests [17]. Intelligence measures remain among of the most reliable and valid predictors of high-level job performance, learning well on the job, and job developmental trajectory, with moderate correlations [18] at all levels of job-complexity. 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 which 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 backgroundof intelligence expression from an epigenetic perspective, Deary et al. [22] have examined (i) molecular genetic (DNA-based) research on intelligence, (ii) the genetic loci associated with intelligence, (iii) DNA-based heritability, and (iv) the genetic correlations of intelligence with other traits based on new brain imaging-intelligence observations that include whole-brain associations and grey and white matter regional definitions [23].

Taking into consideration the consensus from correlational analyses between job performance and IQ-levels, certain conclusions 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 [15] 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].

## 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.

## 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.

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## Author Contributions

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

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