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Vocational Inclinations and Gender Differences of Youth

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1. Abstract

The paper examines the results of a psychometrics battery (combination of questionnaires) for vocational guidance using a sample of 12531 Greek students with an average age of 15.69 years, SD = 1.19, 52.4% females and 47.6% males who completed the questionnaires between 2015 and 2023. The sample base is wide enough since it represents youth from all over the country and can be considered as representative of the population concerned. The questionnaires administered are based on the ARISTON series of psychometric tests, which utilize a unique Expert System for online analysis of the answers given by individuals. The main objectives of the statistical analyses carried out were:

a) Investigate the extent and the nature of gender differences in the sample which represents real cases of individuals.

b) Perform factor analysis between 5 major psychometric scales, in order to search for underlying groupings of their sub-scales.

c)Examine the individual correlations both "inside" these scales (intra- correlations), as well as "outside" them (intercorrelations). The psychometric scales analysed were: Aptitudes-Abilities, Work personality, Vocational inclinations, Self-esteem, and Internal locus of control. Based on these scales, the paper provides evidence for the greater variability hypothesis of males regarding gender differences in occupational interests.

2. Public Significance Statement

This study analyses the fallacy of simplistic stereotypes regarding gender and personality, documenting consistent large gender differences in vocational interests using a large representative sample of Greek students. These findings can provide further understanding on the different career paths men and women tend to follow.

3. Introduction

The vocational battery we studied offers valuable services for vocational guidance, utilizing hundreds of user answers to calculate and interpret a multitude of psychometric scales (Yannakoudakis and Yannakoudakis, 2015) [28]. Over the past four decades (Foudoulaki and Tolis, 2000) [4], this vocational battery has been administered to more than one million individuals all over the world. However, the statistics regarding the personality, aptitudes-abilities and vocational inclinations of the Greek youth have not so far been examined closely and this is the purpose of the current paper. The statistical examination of the results from vocational questionnaires can prove useful mainly in the following three areas:

1. Multivariate psychometric data using a multiplicity of factors and a large representative sample.

2. Research on gender differences across said traits (Hyde, 2014) [10], which can help explore various topics of social importance: from the relationship between culture and evolutionary psychology as related to gender (Schmitt et al., 2016) [23], to a fuller understanding of the causes behind the underrepresentation of women in STEM fields (Stoet and Geary, 2018) [24].

3. Cross-comparisons of a range of psychometric traits, which may lead to improved understanding of their shared underlying structures with applications, particularly in the area of career – vocational counselling (Rúa et al., 2018) [21], which is absolutely vital in these days. The bibliography is currently lacking in aspects, particularly regarding the distribution of the personality in spe-

cific vocational – occupational areas, as is the case with the scale CAPS19 used here.

4. Materials: The Ariston Expert System

The ARISTON psychometric series of questionnaires and inventories utilize an Expert System – based on Artificial Intelligence technology –, which embodies human knowledge regarding personality types, special aptitudes and abilities (Inherent and acquired) and analyses the answers given by an individual using advanced mathematical, statistical and psychometric models. More specifically, the software modules utilize fuzzy logic, advanced classification, clustering and ranking techniques, specialized rules and databases (Yannakoudakis and Yannakoudakis, 2015) [28], in order to analyses several factors, including: a) aptitudes-abilities, e.g. verbal, numerical, mechanical, and diagrammatical reasoning, b) preferences, c) intellectual tasks, d) beliefs, e) values, f) motivations, g) logical reasoning, h) decision-making, i) leadership, j) emotional quotient, etc.

The reports produced by the software contain analytical, quantified results and conclusions regarding the personality of the person examined, supporting decision- making related to a) vocational and career counselling, retrieving specific specializations – professions that match with the personality of the individual out of a database of nearly 3000 entries, b) measurement of aptitudes, c) measurement of abilities, d) measurement of learning styles, e) measurement of learning difficulties, f) personnel assessment, g) personnel selection, h) personnel development, i) performance appraisal, j) development of management, k) employee counselling, l) human engineering, m) productivity analysis, n) administrative skills measurement, o) public relations, p) psychological assessment and support of individuals, q) analysis of psychopathologic traits, etc.

The whole methodology adopted by ARISTON is based on research & development work that started in the early seventies (Foudoulaki and Tolis, 2000) [4] and has been funded by the European Union (program PETRA between 1993 - 1997), as well as by the Greek Ministry of Development (Program PRAXE). The reliability of ARISTON has been validated on 1500 and 500 cases (retest of 250 subjects within 3 weeks), with the aggregated reliability indexes as follows:

•Cronbach coefficient = 0.93

•Spearman Brown = 0.96

•Kuder-Richardson KR-20 = 0.91

•Degree of differentiation = 0.84

•Stochastic entropy of factors = 0.97

•Kappa coefficient = 0.93

Finally, all the data was collected and stored according to standing data protection laws of the European Union (currently GDPR (Voigt and Von dem Bussche, 2017) [27].

5. Main Variables

In the scope of the current paper, we will examine the following psychometric scales provided by ARISTON, which fall under 5 main categories:

1. Holland's scale, one of the most widely used models of vocational interests, as declared by the individual (Holland, 1997; Nauta, 2010) [9,16]. According to the model, the interests can be represented as a hexagon, with edges corresponding to the acronym RIASEC that refers to the 6 basic types: Realistic, Investigative, Artistic, Social, Enterprising, and Conventional. The suffix of the corresponding variables used in this paper is "HOL" (Holland).

2. CAPS19 scale of vocational inclinations, which contains 19 categories for more in depth classification of the inclinations (Papadourakis et al., 2013) [17]. The suffix of the corresponding variables in this paper is "CAPS19". Note the difference between the concept "Interests", as used by the RIASEC scale, and the concept "Inclinations", as used by the CAPS19 scale referring to "Disposition", "Nature", and "Character".

3. Self-esteem scale and subjective social status (peer, school/academic and family environment) (Robins et al., 2001; Salley et al., 2010) [18, 22], in terms of how favorable the individual believes is viewed in each context. The suffix of the corresponding variables in this paper is "SELF_PER" (self-perception).

4. Internal locus of control scale, i.e. the degree to which the individual believes he or she can control the outcomes of his or her life and the environment around them (Kormanik and Rocco, 2009) [11], (Lefcourt, 2013) [12]. The suffix of the corresponding variables in this paper is "CTRL" (control).

5. Aptitudes-Abilities scale, including Numerical, Linguistic, Mechanical and Diagrammatical reasoning. These entail competency regarding: a) ascertainment of the logical sequence of given diagrams and abstract sche-mata, b) determination of sequences or series of elements that are in some way connected to each other (numerically or lexically), c) application of rules for inductive inference and drawing of conclusions, d) flexibility with abstract thought, e) data analysis, which aims at detecting inherent relationships, f) detecting common features of data and the establishment of new groups of data (Yannakoudakis and Yannakoudakis, 2015) [28]. The suffix of the corresponding variables in this paper is "APT" (aptitude).

6. Secondary Variables

All the data was collected and stored according to standing data protection laws of the European Union regarding personal data, which were anonymized before extraction of the information we needed for statistical analyses. The data we analyzed also contain the time duration taken for the completion of the questions of each scale (prefix "DUR"). Specifically, for CAPS19 and self-perception, a truth score is present as well, i.e. the reliability of the answers, calculated utilizing stochastic processes (Cox, 2017) [2] where several questions are correlated and cross-referenced by the Expert System (prefix "Truth Score"). The truth scores are used to correct the expected error of the measurement of the scales, according to the norms established by the results of the rest of the sample. Gender is indicated as 1 for female and 0 for male. Thus, a positive correlation on gender indicates a trend for females, and vice versa. Finally, the software used for the statistical processing of the data was IBM SPSS 23, R 3.6.2, Python 2.7 and Excel 2019.

7. Methods

7.1. Challenges of Measuring Gender Differences

The measurement of gender differences presents multiple challenges and limitations (Del Giudice, 2019) [3]. The most commonly used corresponding metric is Cohen's d, which can accumulate bias from skewed distributions of the measured factor, differing gender variability, measurement error, small sample sizes, presence of outliers. Furthermore, in our case, none of the variables passes the criteria of the Kolmogorov- Smirnov test for normality (0.001 level), i.e. their distributions are skewed and or display kurtosis (Lilliefors, 1967) [13]. However, most of these limitations are irrelevant to our analyses due to our sample size of 12531 subjects, which brings the bias of non-normality down to negligible levels. There is evidence to suggest that regardless of the degree of distribution skewness (see Figure 1), for samples larger than 100 cases, the respective bias approaches zero (Rousselet, 2018) [20].

Our sample size also mostly eradicates the effect of outliers. As for the measurement error, we address it by using truth scores and correcting the scales accordingly (as explained in the section Materials: Secondary Variables).

Lastly, as we will see in a following section (Results: Gender differences), the variability of each sub-scale we examine differs only relatively slightly between genders. Cohen's d is robust to such small differences, and they would only constitute an issue for the measurement of tail rations, which we will not use (Del Giudice, 2019) [3].

Apart from median effects sizes of gender differences of the sub-scales, we will also report Mahalanobis D regarding the whole scales, which provide a significantly more informative picture of global effects than aggregates (we will utilize R functions (Giudice, 2019) [6] for the calculation). However, D exhibits bigger concerns than d regarding its accuracy. As a rule of thumb, research results (Giudice, 2013) [5] propose at least 100 cases per variable used in D, which our analysis satisfies confidently, since the most sub-scales our dataset contains is 19 (corresponding to 1900 subjects). However, the rule guarantees low bias approximately for values of $D \geq 0.45$, and therefore we will point out any results near this threshold. Also, we will report Probability of Correct Classification (PCC) estimates based on the aforementioned effect sizes, as PCC constitutes one of the most intuitive ways of understanding the magnitude of gender differences (Del Giudice, 2019) [3]. In what follows (Figure 2) we provide a graph showcasing the relationship between effect size (ES) and PCC. ES=0 corresponds to PCC=.5, meaning that when the distribution of some factor is identical in both genders, the probability of correctly guessing the gender of randomly selected person from the sample is 50%. ES=.5, which corresponds to about PCC = .6. As the effect size is getting larger, PCC approaches 1 (but never reaches it). Lastly, we will report the effect size of gender differences on the people-ideas dimension, as described in previous research (Prediger, 1982) [17] and usually reported in relevant research ever since.

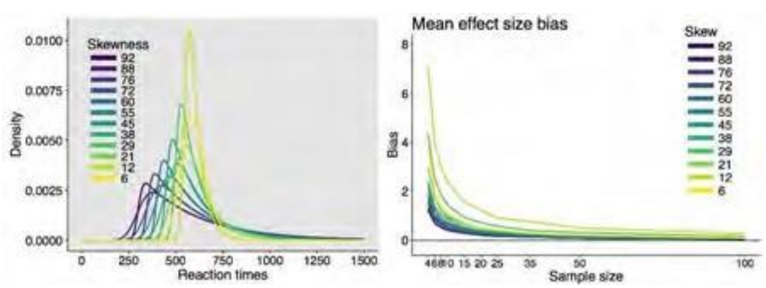

Figure 1: Distribution skewness, sample size, and bias of the effect size

Note: In all categories, for samples sizes larger than 100, the respective bias approaches zero. Source: (Rousselet,2018) under CC BY-SA 4.0.

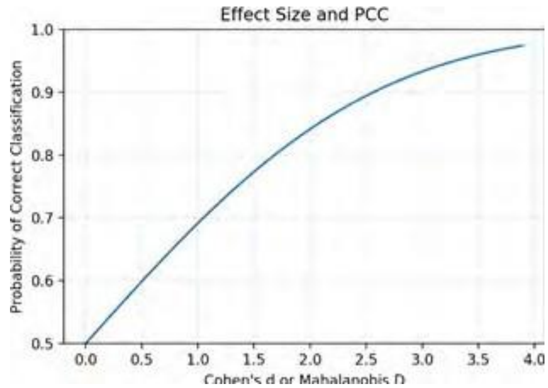

Figure 2: Effect size and Probability of Correct Classification

Note: The relationship between the effect size (such as Cohen's d or Mahalanobis D) between two populations, and the probability that a randomly selected individual of either population will be correctly classified to their corresponding population. This was computed using Python 2.7.

8. Results

8.1. Gender Differences

For a background on the following section, please refer to the previous one: Methods: Challenges of measuring gender differences. On (Table 1), we can see the mean and SD scores of all the variables by gender, as well as their gender variance ratios (values larger than 1 imply larger variance of males). Using the data of (Table 1) we can view the most preferred work environments of each gender by sorting them in bar graphs (Figure 3): Returning to the overall picture of (Table 1), we note that variance ratios of the genders correspond to a mean of 1.08, with only 2 variables larger than 1.5 (Computing_CAPS19 reaches 2.12 and Mechanical_CAPS19 reaches 1.7). Therefore, according to (Del Giudice, 2019) [3], the corresponding bias in the vast majority of effect sizes we will now report is relatively negligible. On (Table 2) we can examine the effect sizes of the differences of all the variables between the genders (positive values indicate larger effects for females). We provide the effect sizes in descending order by absolute value, so that the largest and lowest differences stand out. For example, the largest differences correspond to computing, mechanical and overall realistic vocational inclinations (d=-1.01 to -0.92, with some reservation for the first two, as noted earlier), and the smallest to school self- perception, architectural inclinations and diagrammatical aptitude (d=.02 to 0.0). As reported previously, we also provide probability of correct classification (PCC) estimates for a more intuitive interpretation of the magnitude of differences. Now, on (Table 3) we can see the overall differences for the 4 of the scales that are multivariate, utilizing Mahalanobis D effect sizes. We note similar values for our 2 vocational scales, D=1.27 for RIASEC and D=1.44 for CAPS19. As mentioned earlier, we point out that the effect size for Aptitudes-Abilities and Self-Perception is near the threshold of 0.45, so these values may present substantial bias. Lastly, the effect size of gender differences on the people-ideas dimension of our sample is d=-1.00.

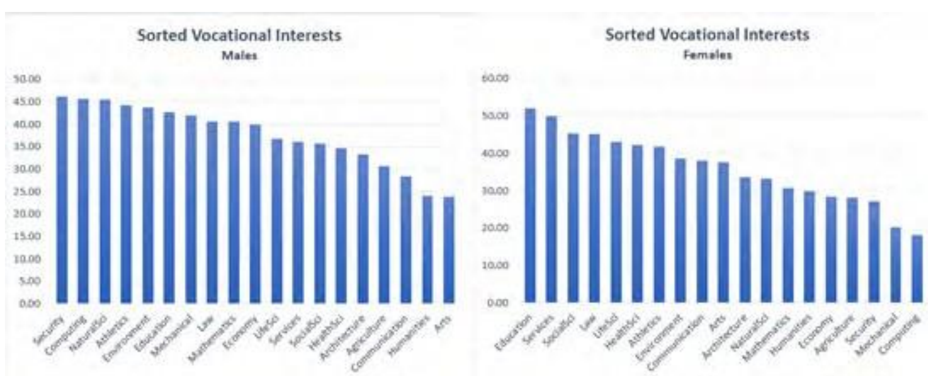

Figure 3: Sorted vocational interests by gender

Note: The vocational inclinations of males and females in our sample, sorted from higher to lower score, according to the vocational categories of CAPS19.

Table 1: Mean and SD scores of all variables by gender, and corresponding gender variance ratios

	0 (Male)		1 (Female)		
	Mean	SD	Mean	SD	Variance Ratios
Computing_CAPS19	45.66	31.823	18.18	21.836	2.12
Mechanical_CAPS19	42.07	26.703	20.21	20.456	1.7
Security_CAPS19	46.2	26.645	27.09	21.937	1.48
Lang_APT	76	17.167	80.94	15.09	1.29
Realistic_HOL	53.66	26.018	29.22	22.898	1.29
Economy_CAPS19	39.86	28.522	28.45	25.156	1.29
TruthScore	82.92	10.413	83.87	9.188	1.28
TruthScore_CAPS19	86.51	8.576	87.05	7.733	1.23
Agriculture_CAPS19	30.75	25.725	28.13	23.23	1.23
TruthScore_SELF_PER	79.37	17.217	80.7	15.574	1.22
Architecture_CAPS19	33.26	25.124	33.7	22.81	1.21
NaturalSci_CAPS19	45.5	30.452	33.28	27.788	1.2
Mathematics_CAPS19	40.62	25.36	30.74	23.228	1.19
DUR_CAPS19	1090.45	335.692	1048.06	311.501	1.16
Social_HOL	58.88	21.713	69.25	20.201	1.16
DUR_riasec	502.46	159.719	492.1	152.231	1.1
Diagr_APT	67.29	17.789	68.03	16.997	1.1
DUR_contr	304.1	92.558	288.14	89.04	1.08
Athletics_CAPS19	44.25	30.2	41.82	29.338	1.06
Environment_CAPS19	43.84	27.429	38.64	26.749	1.05
Peer_SELF_PER	80.55	18.776	79.58	18.319	1.05
DUR_self1	323.85	99.397	311.36	97.557	1.04
SocialSci_CAPS19	35.65	24.026	45.38	23.636	1.03
Duration	3385.62	794.571	3315.43	787.083	1.02
Age	15.7	1.186	15.72	1.187	1
Mecha_APT	58.68	16.411	55.48	16.518	0.99
Internal_CTRL	69.91	10.07	68.72	10.219	0.97
Numeric_APT	78.36	20.708	75.11	21.022	0.97
Communication_CAPS19	28.39	23.267	38.13	23.826	0.95
Law_CAPS19	40.67	26.201	45.22	26.954	0.94
Services_CAPS19	36.15	28.032	49.99	28.926	0.94
Enterprising_HOL	64.92	22.888	60.54	23.641	0.94
Investigative_HOL	55.91	28.236	51.29	29.261	0.93
Conventional_HOL	37.41	18.417	38.54	19.267	0.91
Education_CAPS19	42.71	25.257	52.16	26.67	0.9
Family_SELF_PER	62.99	23.61	60.52	25.215	0.88
LifeSci_CAPS19	36.85	30.13	43.13	32.653	0.85
Selfesteem_SELF_PER	76.24	14.917	70.46	16.335	0.83
HealthSci_CAPS19	34.6	27.64	42.3	30.462	0.82
Humanities_CAPS19	24.08	23.223	29.89	25.647	0.82
Artistic_HOL	31.51	22.773	44.86	25.709	0.78
School_SELF_PER	63.24	23.569	63.36	26.691	0.78
Arts_CAPS19	23.94	23.701	37.65	28.435	0.69

Note. Values larger than 1 imply larger variance of males.

Table 2: Effect sizes of gender differences and corresponding PCC

	Cohen's d	PCC
Computing_CAPS19	-1.01	69.27%
Realistic_HOL	-1	69.10%
Mechanical_CAPS19	-0.92	67.71%
Security_CAPS19	-0.78	65.23%
Artistic_HOL	0.55	60.83%
Arts_CAPS19	0.52	60.33%
Social_HOL	0.49	59.76%
Services_CAPS19	0.49	59.60%
Economy_CAPS19	-0.42	58.40%
NaturalSci_CAPS19	-0.42	58.30%
Communication_CAPS19	0.41	58.19%
SocialSci_CAPS19	0.41	58.09%
Mathematics_CAPS19	-0.41	58.05%
Selfesteem_SELF_PER	-0.37	57.32%
Education_CAPS19	0.36	57.22%
Lang_APT	0.31	56.08%
HealthSci_CAPS19	0.26	55.26%
Humanities_CAPS19	0.24	54.73%
LifeSci_CAPS19	0.2	53.98%
Mecha_APT	-0.19	53.88%
Environment_CAPS19	-0.19	53.82%
Enterprising_HOL	-0.19	53.74%
DUR_contr	-0.18	53.50%
Law_CAPS19	0.17	53.41%
Investigative_HOL	-0.16	53.20%
Numeric_APT	-0.16	53.10%
DUR_CAPS19	-0.13	52.61%
DUR_self_per	-0.13	52.53%
Internal_CTRL	-0.12	52.34%
Agriculture_CAPS19	-0.11	52.13%
Family_SELF_PER	-0.1	52.02%
Duration	-0.09	51.77%
Athletics_CAPS19	-0.08	51.63%
TruthScore_SELF_PER	0.08	51.62%
DUR_riasec	-0.07	51.32%
TruthScore_CAPS19	0.07	51.32%
Conventional_HOL	0.06	51.19%
Peer_SELF_PER	-0.05	51.04%
Diagr_APT	0.04	50.84%
Age	0.02	50.37%
Architecture_CAPS19	0.02	50.37%
School_SELF_PER	0	50.10%

Note. The effect sizes of gender differences for all the variables and their corresponding probabilities of correct classification (i.e. the probability that a randomly selected individual from our sample would be categorized correctly as male or female based on their score on the corresponding variable).

Table 3: Mahalanobis D of gender differences and corresponding PCC

	Mahalanobis D	PCC
Holland's RIASEC	1.27	73.81%
CAPS19	1.44	76.42%
Aptitudes-Abilities	0.5	59.95%
Self-Perception	0.44	58.71%

Note. Multivariate effect sizes of gender differences for the 4 applicable scales and their corresponding probabilities of correct classification (i.e. the probability that a randomly selected individual from our sample would be categorized correctly as male or female based on their score on the corresponding subscales). The D variables were computed utilizing R functions from (Giudice, 2019) under CC BY 4.0.

8.2. Factor Analysis

In order to search for underlying grouping constructs of our 5 scales, we performed a factor analysis between all of them (Thompson, 2004) [26] with the K1 criterion (one of the most commonly used (Hayton et al., 2004) [8], and the result was the top 10 factors most able to explain the relationships between the variables. More details about the metrics of this process are available on the Tables A.1 and A.2 of the Appendix. (Table 4) presents the correlations of each variable with each of the 10 factors, thus indicating the best grouping fitted to the variables (for clarity, values lower than .1 are suppressed). For instance, the grouping most appropriate to explain the variability of the scales (factor 1), can be summarized as follows: it corresponds mostly to male individuals, to mechanical inclinations and overall realistic type interests ('doers' who like to work with 'things'); it corresponds slightly to self-esteem; it does not correspond to humanities fields; and it corresponds slightly with less language aptitude. Due to the numerosity of our subscales and their complex relationships, it is hard to provide a comprehensive summary of the groupings. For the detailed characteristics of them, the reader can refer to (Table 3). We will provide a further examination of the results on the section Discussion and Conclusions.

Table 4: Correlation matrix between all the variables and factors

Variable	1	2	3	4	5	6	7	8	9	10
Duration			0.934						0.105	
Age		0.118		-0.135	-0.237		-0.168		0.279	0.326
Gender	-0.716			0.22		0.315				
TruthScore								0.987		
Realistic_HOL	0.819	-0.112		0.207	0.162	0.145				
Investigative_HOL	0.361			0.786					0.18	-0.133
Artistic_HOL		0.375				0.808				
Social_HOL	-0.146	0.552		0.274	0.161	0.172				0.378
Enterprising_HOL	0.217	0.358	-0.101	0.704		0.115				
Conventional_HOL		0.153	0.132	0.704	0.135			-0.119		0.132
Architecture_CAPS19	0.374	0.268		0.129	0.4	0.531				
Arts_CAPS19		0.27				0.845				
Athletics_CAPS19	0.143	0.203		0.147	0.177	0.128				0.726
Agriculture_CAPS19	0.375	0.193		0.306	0.176	0.448				0.319
Communication_CAPS19		0.823			0.284	0.259				
Computing_CAPS19	0.785			0.134	0.157					
Mathematics_CAPS19	0.506	0.117		0.408	0.496				0.14	
Services_CAPS19		0.366			0.499	0.382				0.414
SocialSci_CAPS19		0.84		0.112	0.161	0.18				0.181
Economy_CAPS19	0.359	0.296			0.76		0.111			
Education_CAPS19		0.553		0.138	0.18	0.282				0.46
Law_CAPS19		0.822			0.269					
LifeSci_CAPS19	0.116			0.902						

Security_CAPS19	0.683	0.244		0.183	0.12					0.252
Environment_CAPS19	0.484	0.17		0.588		0.316				
HealthSci_CAPS19		0.153		0.809						0.277
Humanities_CAPS19		0.792				0.343				
Mechanical_CAPS19	0.846			0.286	0.171	0.184				
NaturalSci_CAPS19	0.586			0.68		0.114			0.113	
Lang_APT	-0.154			0.103				0.113	0.708	
Numeric_APT									0.779	
Diagr_APT									0.706	
Mecha_APT	0.132	-0.13						0.429	0.21	
Internal_CTRL							0.688		0.209	-0.103
Family_SELF_PER							0.637			
School_SELF_PER				0.172		0.669			0.125	-0.127
Peer_SELF_PER				-0.106			0.634			0.283
Selfesteem_SELF_PER	0.136					-0.104	0.818			
TruthScore_CAPS19							0.236	0.565	0.166	-0.133
TruthScore_SELF_PER							-0.105	0.885		
DUR_Contr			0.849							
DUR_RIASEC			0.884							
DUR_Self_Per			0.838							
DUR_CAPS19			0.826							

Note. The correlations indicate the best grouping fitted to the variables. For clarity, values lower than .1 are suppressed. Rotation Method: Varimax with Kaiser Normalization.

8.3. Intra-correlations and Intercorrelations

In order to investigate more individual relations between the scales, we performed bivariate correlations. Firstly, we will provide a summary of intra-correlations, i.e. correlations between the items of each scale, and then intercorrelations, i.e. correlations between the items of all distinct scales. As scales 1 and 2 (RIASEC and vocational categories – CAPS19) are considered interchangeable, we calculated two correlation matrices between each of these scales and the rest of them (Tables 5 and A.3 of the Appendix). Due to the numerosity of the CAPS19 subscales and its overlap with RIASEC, we put the CAPS19 matrix in the Appendix and will exclude it from both of our summaries.

Here we review and summarise intra-correlations in between the following subscales:

•Hollands's RIASEC: relatively high correlations between realistic and investigative types (.48), as well as between enterprising and conventional (.43), somewhat less between artistic and social types (.38) as well as social and conventional (.36), lesser between social and enterprising (.3), and the rest relatively low (<.26).

•Aptitudes-Abilities: relatively high correlations between linguistic and numeric (.47), as well as between numeric and diagrammatical (.46), while lesser between language and diagrammatical (.35), and the rest relatively low (<.2).

•Self-perception: relatively high to moderate between all 4 of them (.48-37), except between peer and school (.28) as well as family and peer (.19).

Here, we review and summarise the noteworthy intercorrelations (larger than 0.18 and excluding duplicate mentions) regarding:

•Hollands's RIASEC: low correlations between the investigative type and numeric aptitude (.23), as well as between the enterprising type and positive peer self-perception (.19).

•Aptitudes-Abilities: low correlation between numeric and internal locus of control (.21).

•Locus of control: relatively high to moderate correlations between internal locus of control and all self-perception types (.48 to .35).

•Self-perception: no other noteworthy correlations.

We also performed separate correlations between our secondary variables (age, total and scale specific duration, and truth scores) and our main variables (5 scales). We noted no substantial correlations, with the highest being .18 between the Truth Score and the Agriculture sector of the CAPS19 scale (Table A.4 of the Appendix).

Table 5: Correlation matrix of RIASEC and the other 3 main scales

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Realistic_HOL	1	.481**	.083**	.022*	0.241**	.257**	.049**	.125**	.088**	.098**	.045**	.025**	.021*	.021*	.096**
2. Investigative_ HOL	.481**	1	.083*	.135**	0.078**	.146**	.128**	.228**	.192**	.087**	.124**	.025**	.178**	.044**	.034**
3. Artistic_HOL	.083**	.083**	1	.382**	0.155**	.165**	.030**	081**	0.003	.052*	.084**	.085**	.073**	.044**	.164**
4. Social_HOL	.022*	.135**	.382**	1	0.3**	.356**	-0.002	.093**	.068**	.074**	-0.015	.033**	.045**	.092**	.048**
5. Enterprising_ HOL	.241**	.078**	.155**	.300**	1	.427**	.018*	.057**	0.017	-0.005	.110**	.022*	.086**	.192**	.135**
6. Conventional_ HOL	.257**	.146*	.165**	.356**	0.427	1	.029*	.032*	.029*	.036**	.041**	.079**	.036**	-0.008	.030**
7. Lang_APT	.049*	.128**	.030**	-0.002	0.018*	.029**	1	.472**	.355**	.133**	.163**	0.014	.170**	.041**	.031**
8. Numeric_APT	.125**	.228**	.081**	.093**	0.057**	.032**	.472**	1	.460**	.198**	.216*	0.33*	.168*	.042*	.096*
9. Diagr_APT	.088**	.192**	0.003	.068**	0.017	.029**	.355**	.460**	1	.163**	.151**	-0.008	.104**	0	.035*
10. Mecha_APT	.098**	.087**	.052**	.074**	0.005	.036**	.133**	.198**	.163**	1	.077**	0.014	.038**	.026**	.043**
11. Internal_ CTRL	.045**	.124**	.084**	-0.015	0.11**	.041**	.163**	.216**	.151**	.077**	1	.344**	.334**	.336**	.482**
12. Family_ SELF_PER	.025**	025**	025**	025**	0.022**	.079**	0.014	.033**	-0.008	0.014	.344**	1	.325*	.187**	.373**
13. School_ SELF_PER	.021**	.178**	.073**	.045**	0.086**	.036**	.170**	.168**	.104**	.038**	.334**	.325**	1	.279**	.473**
14. Environment_ SELF _PER	.021**	.044**	.044**	.092**	0.192**	-0.008	.041**	.042**	0	.026**	.336**	.187**	.279**	1	.479**
15. Selfesteem_ SELF_ PER	.096**	.034**	.164**	.048**	0.135**	.030**	.031**	.096**	.035**	.043**	.482**	.373**	.473*	.479**	1

Note. A single asterisk indicates significance at the 0.05 level, whereas two asterisks indicate significance at the 0.01 level. Virtually all noteworthy correlations are significant at the 0.01 level.

9. Discussion and Conclusion

One of the topics our paper contributes to is the greater male variability hypothesis, according to which males display greater variability in traits than females. This hypothesis is socially significant because it would indicate that even with the assumption that males are on average equally able on an area as females, males would still be expected to be overrepresented on the top level of achievement of this area. There is evidence to suggest that males tend to have higher variance on mathematical and verbal abilities, but females tend to have higher variance on fear and emotionality (Hyde, 2014) [10]. Also, following an examination of 12 databases from the International Association for the Evaluation of Educational Achievement and the Program for International Student Assessment for the years 1995-2015 (Baye and Monseur, 2016) [1], there is evidence to suggest that, on average, boys showed 14% greater variance than girls in science, reading, and math test scores. Contrary to a previous metanalysis, the effect was virtually universal among countries. These results were subsequently replicated (Gray et al., 2019) [7], noting that policies leading to greater female participation in the workforce tended to increase female variability and decrease the gap. On the other hand, the results were complicated by the finding that better Educational Attainment for women was correlated with a widening of the gap in mathematics and science literacy. As for our findings: firstly, we present the gender differences in variability for all the variables. Our data provide mixed overall evidence for the gender variability hypothesis: the mean variance ratio was 1.08 and the median 1.04 (very slightly favoring males). On 19 out of our 44 variables, females presented greater variability, notably on arts, humanities and life sciences inclinations, as well as self-esteem and school self- perception (0.69 to 0.85). On the other hand, males displayed even greater variability on computing and mechanical inclinations (2.12 and 1.7), and lesser but still large variability on security inclinations, language aptitude and overall realistic interests (1.48 to 1.29). The topic of gender differences in academic tests also presents social significance. However, as our corresponding questions are not aiming to examine high level concepts but basic inclinations, direct comparisons with international tests such as PISA are not suitable. Nevertheless, our results are consistent with similar tests (females tend to score better on language, whereas males on numeric and mechanical tests, albeit the differences are less than moderate) (Hyde, 2014) [10]. Next, our paper reports on vocational preferences, which present social significance e.g. as one of the factors in the assessment of systemic bias regarding the gender ratios of participation in occupational fields. Our results are consistent with the most recent metanalysis (Su et al., 2009) [25] with

503,188 participants, and also the largest relevant study (Morris, 2016) [15] with more than a million participants in the USA. Remarkably, the latter found only very small ethnicity effects, consistent with a sample of 200,000 participants from 53 nations (Lippa, 2008) [14] and found that females were more interested on people and male on things in all of them. The differences were unrelated to gender equality and mostly invariant between countries.

Our research deals with an area that has not been studied before, providing an overall estimation of gender differences on occupational inclinations of Greek youth, utilizing several measures including Mahalanobis D (usually the gender difference on the dimension of people and things (Prediger, 1982) is reported as an overall metric). Our finding of D=1.27-1.44 is close to the finding of disattenuated D=1.61 in an aforementioned study (Morris, 2016) [15]. As described in Section Materials: Secondary Variables of this paper, we attempted error correction on the variable values, whereas earlier research (Morris, 2016) [15] attempted error correction on the effect sizes, which may account for part of the difference. The gender differences in this area seem to be one of the most robust among all the psychometrical gender differences, and this is echoed by our factor analysis, where the primary factors explaining the variability of our 5 scales heavily depended on, namely factors #1, #4 and #6 of. However, our factor analysis also documented the fallacy of simplistic stereotypes: despite that realistic and investigative interests in the RIASEC scale are more characteristic of males on average (d=-1 and -.16), factors #4 and #6 indicate that a subset of the female population tends to present specific interest for these same areas. It should be noted though that even in these cases, other general trends in occupational inclinations are not contradicted: the #4 trend for investigative interests mostly refers to the health and life sciences, while the #6 trend for realistic interests is weak and overshadowed by the simultaneous robust trend towards artistic interests.

Still, the overall picture of gender differences in the 3 scales, excluding CAPS19, show the inaccuracy of generalizations: the gender differences in our sample are estimated to provide less than 10% of additional predictive ability of the gender of a randomly selected individual, based on their score in one of the scales (e.g. with PCC=58.71% of self-perception, an additional 8.71% of predictive ability). We consider that such small effects are observable only in large group averages and are not useful as a guide in any one-by-one setting. Moving on to the next topic, first of all we note that our intra-correlations between RIASEC are consistent with the metanalysis carried out by recent research (Rúa et al., 2018) [21]. Then, we note that the correlations between aptitudes-abilities and the corresponding occupational inclination types are rather unexpectedly weak: in all cases lower than .13, whereas a previous metanalysis of 36,154 people (Rottinghaus et al., 2003) [19] provided much higher correlations (.48-.76). We attribute the difference to the diverging type of ability tests used (the ARISTON battery analyses inherent inclinations whereas the SII/SCI and CISS of the metanalysis analyses simple skills). On a parallel topic, examining the CAPS1 9 and aptitudes-abilities correlations we note a systematic difference the correlations are significantly stronger for the corresponding numeric aptitudes than for the corresponding language aptitudes (e.g. natural sciences: .18, mathematics: .19, humanities: .03, law: .07). This finding could be an artefact of our specific psychometric questionnaires, but it could also indicate some intrinsic difference between the two cases. As for the correlations between the scales, the most noteworthy one is the virtually stable correlations of locus of control with all the self-perception types, as well as the generally stable correlations amongst the self-perception types themselves. In further clarification of this, our findings indicate a trend for the individuals who believe that they dictate their own future, to also show consistently positive increases in all peer, school and family self-perceptions, and even more positive regarding self-esteem. Our results also indicate that an individual who tends to hold positive or negative self- perception in one of the 4 types (peer, self, family, school), tends to do so for the rest of the types as well. To conclude, the literature is limited on psychometric studies with large Greek samples, and more are needed for different age groups at both regional as well as international context. On these grounds, we consider our results useful in the area of social studies generally.

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