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A Spatial Analysis of Sex Differences in Chess Expertise Across 24 Countries in Eurasia

Angel Blanch[1], Carles Comas[2]

[1]Department of Psychology, University of Lleida, Spain
[2] Department of Mathematics, University of Lleida, Spain

Correspondence: Angel Blanch, angel.blanch@udl.cat; Carles Comas, carles.comas@udl.cat

Abstract

Past reports attribute sex differences in chess expertise to either the differential participation of males and females in chess, or to biological and cultural factors. This study examines whether geographical factors relate with the sex gap in chess expertise evaluated with three measures: raw (R), expected (E), and discrepancy (D). These differences corresponded to the 100 top-ranked male and female chess players in 24 Eurasian countries. The main aim of the study consisted of evaluating whether these countries resembled or differed in the three measures (RED) regarding either country size or country latitude. While no differences or similarities were found regarding latitude, six countries of a similar size resembled the expected sex differences (E) in chess expertise. Five out of these six countries share geographical borders, linguistic origins, and climatic characteristics, Slovenia, Croatia, Serbia, Bulgaria, and Greece. The outcomes in the current study suggest that bearing in mind geographical factors is a worthy research avenue to address the prevalent sex gap in chess expertise across different countries and cultures.

Keywords

Chess expertise, sex differences, spatial statistics

Introduction

Sex differences in chess expertise tend to be large, with males scoring higher than females in the Elo chess rating (Elo, 1978; Glickman, 1995). Past reports attribute these differences either to the remarkable differential participation of males and females in chess (Bilalic et al., 2009; Chabris & Glickman, 2006; Charness & Gerchak, 1996), or to biological and cultural factors (Blanch et al., 2015; Howard, 2014a, 2014b). The topic has stimulated fruitful controversy and debate (Bilalic & McLeod, 2006, 2007; Howard, 2005).

Participation rates appear important to explain sex differences in chess performance and chess expertise. One of the first studies in this field proposes a statistical model (MILL7) supporting that some group differences in chess performance, including males and females, depend on the differences in the number of participants across groups (Charness & Gerchak, 1996). Subsequent studies argue that the sex discrepancy in the participation of males and females at the highest level of chess expertise depends in turn on the sex discrepancy in the participation of males and females when starting chess playing (Chabris & Glickman, 2006), or to different inclusion criteria of males and females in rating lists (Bilalic & McLeod, 2007). Another study contrasting sex differences in chess expertise with German players (Bilalic et al., 2009), highlights that a substantial 96% of the observed differences depends on the larger number of males compared with females.

On the other hand, other evidence suggests that the disparity in chess expertise among males and females depends on biological and cultural factors. Studies with extensive samples with thousands of chess players suggest that, on average, males might hold an innate advantage in chess expertise (Howard, 2005, 2014b) that might vary, however, depending on cultural or country differences such as when contrasting male and female chess players from Georgia (Howard, 2014a). Moreover, evidence based on chess tournaments suggest age and practice as better predictors of the sex differences in chess expertise than the discrepancy in the number of males and females (Blanch et al., 2015).

Because this sex discrepancy in chess expertise is analogous to that found in several fields, most notably in science, technology, engineering, and mathematics (STEM), but also in later achievements in life (Benbow, 1988; Benbow et al., 2000; Benbow & Stanley, 1980; Lubinski et al., 2014; Wai, 2013; Wai et al., 2010), other biological and cultural factors apart from participation rates could certainly contribute to explain sex differences in chess expertise (Blanch, 2021). An alternative method to evaluate the differences due to differential participation rates (Knapp, 2010), reports that only the 67% of the differences in chess expertise is explained by the different number of males and females with the same data set reporting a sharply diverging outcome (Bilalic et al., 2009). The application of this novel method in a cross-cultural study with the top-hundred ranked male and female chess players in 24 Eurasian countries, suggests sex gaps in chess expertise that are unrelated to different participation rates of males and females (Blanch, 2016).

This method implies the sampling without replacement from a negative hypergeometric distribution, which is more appropriate to estimate the sex differences in the Elo ratings at the upper tail of the distribution while contemplating the sex discrepancy in the participation rates (Zhang & Johnson, 2011). This approach provides data in three main indicators of the sex gap in chess expertise (Raw, Expected, and Discrepancy, RED). The raw (R) difference is the male – female difference when comparing the male-female lists (k = 100) ordered in descending order of the Elo rating. The expected (E) Elo rating difference indicates the percentage of raw differences explained by differential participation rates. The discrepancy (D) indicates the difference between the two previous curves (R and E). The main outcomes by applying this method (Blanch, 2016) underline that the differential sex ratios across countries explained only in part the sex gap in chess expertise. Moreover, there is considerable variability in RED across countries that might depend on geographical and cultural factors.

The effect of such distal factors, however, has been rather unexplored in expertise research. Geographical variation arises in psychological and behavioral characteristics. For example, geographical differences have been explored within the United States regarding the big five personality factors of extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience (Rentfrow et al., 2008). Moreover, systematic trends in psychological characteristics such as creativity, aggressiveness, or individualism, appear to vary with geographical latitude (Van de Vliert & Van Lange, 2019). This sort of geographical differences may also comprise expertise in sports (Rothwell et al., 2018) and eventually regarding the observed sex gap in chess expertise. For instance, risk-taking, conservative, and mixed chess playing strategies might emerge in top-level chess when comparing different civilizations (Chassy & Gobet, 2015).

The study by Blanch (2016) suggests that countries with narrower sex gaps in chess expertise appear to predominate in small sized or Eastern European countries (Georgia, Czech Republic, Romania, Hungary, or Slovakia). On the other hand, countries with wider sex gaps in chess expertise are larger or predominate in southern Europe (Greece, Russia, Bulgaria, Croatia, Portugal, or France). Figure 1 shows that the discrepancy (D) measure appears to be higher in larger or more southern countries, while being lower in smaller or more northern countries, particularly in central Europe.

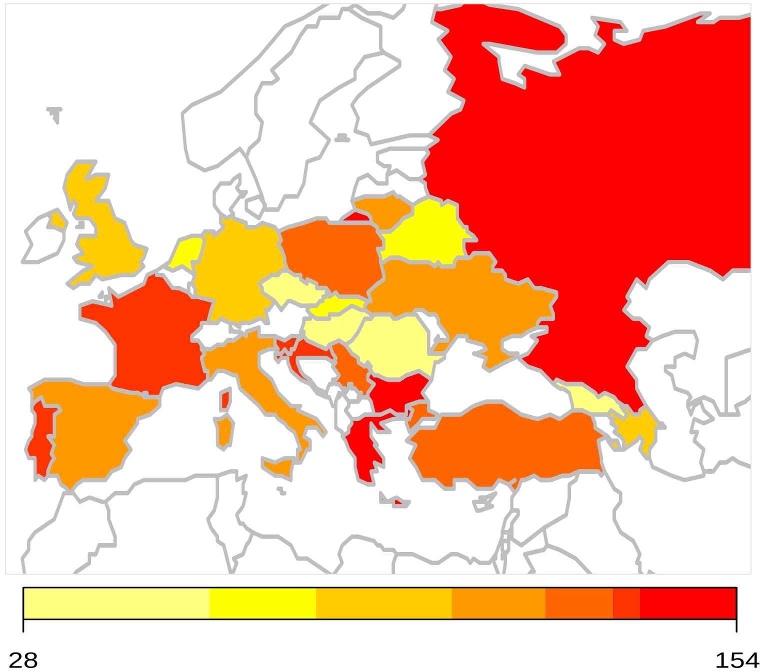

Figure 1. Discrepancy in actual and estimated sex differences (D) in Elo points for 24 Eurasian countries.

In the current study, we reanalyzed this data with spatial statistics methods to address whether sex differences in chess expertise followed such geographical patterns. More specifically, we evaluated the spatial autocorrelation structure of RED considering country latitude and country size, assessing whether the occurrence of RED could be accounted for by randomness alone or by latitude and country size (Anselin, 1995; Fortin & Dale, 2005). According to the findings in Blanch (2016), non-random spatial structures could be expected regarding the geographical proximity of countries (i.e., latitude) and the country size. Hence, we explored whether the countries with a higher similarity in latitude and size displayed more similarities in RED. Conversely, we also evaluated whether higher dissimilarities in latitude and size associated with higher dissimilarities in RED.

Method

Elo Rating Data

The data from Blanch (2016) was reanalyzed here, which corresponded to the March 2014 Elo rating list (FIDE) with over 400,000 male and female chess players from 170 countries. Because of several countries had only a limited number of female chess players, only countries from the Eurasian region with at least 100 women were selected (n = 24). The study sample comprised 102,774 males and 9,484 females (n = 112,258), with a male to female ratio of 11:1 that varied between 2:1 for Georgia, and 26:1 for Italy.

Table 1 summarizes the data for the analyzed countries indicating the number of males and females, male to female ratio (M:F), mean Elo ratings of males and females, country latitude in degrees with decimals, country size in square miles, and the three types of sex differences in chess expertise: raw (R), estimated (E), and discrepancy (D). The three measures used to calibrate the sex gap in chess expertise were obtained from the Elo ratings of the top-ranked 100 males compared with the top-ranked 100 females (k = 100) for each selected country (n = 24). The raw differences (R) indicate the difference $R_k = EloM_k – EloF_k$ for each k-pair (EloM for each k-male, and EloF for each k-female). The expected differences (E) indicate the percentage of raw differences explained by the male-female differential participation rates. These differences were obtained from the expected ranking position of each female player in the combined list of males and females, and with the expression $E = (E_k / R_k) * 100$. The discrepancy measure (D) indicates the level of agreement between the R and E curves for each of the 100-k male-female pairs (D = R – E), with higher values supporting factors other than participation rates as eventual causes of the sex gap in chess expertise.

Table 1. Sex differences (M: Males, F: Females) in chess expertise according with raw (R), estimated (E), and discrepancy (D) measures in 24 Eurasian countries. The countries are ordered from lower to higher male to female ratios (M:F).

Country		M	F	M:F	Mean Elo rating M	F	Latitude	Sq Miles	Mean by country R	E	D
Georgia	GEO	436	200	2	2367	2151	42.1685594	26,911	216	86	28
Azerbaijan	AZE	439	134	3	2353	1961	40.2882767	33,436	389	78	84
Belarus	BLR	507	116	4	2335	1948	53.5313115	80,155	362	78	74
Lithuania	LTU	514	123	4	2286	1867	55.3261108	25,212	422	73	104
Bulgaria	BUL	5589	912	6	2415	1991	42.7688999	42,823	423	66	138
Poland	POL	921	149	6	2467	2159	52.1275954	120,725	308	61	121
Russia	RUS	14560	2381	6	2618	2309	61.9805217	6,592,846	306	53	143
Romania	ROU	846	124	7	2414	2103	45.8524294	91,699	311	82	55
Slovenia	SLO	2046	303	7	2327	1877	46.1155544	7,827	446	71	134
Ukraine	UKR	2423	342	7	2542	2217	48.9965678	233,090	325	67	107
Greece	GRE	2743	347	8	2330	1922	39.0746697	50,944	409	63	154
Turkey	TUR	2028	204	10	2281	1793	39.0616034	300,948	486	73	131
Hungary	HUN	4413	377	12	2462	2140	47.1627771	35,920	323	85	58
Portugal	POR	3195	276	12	2219	1612	39.5955025	35,603	607	76	137
Serbia	SRB	1154	100	12	2456	2118	44.2215031	34,116	338	64	122
France	FRA	11644	930	13	2472	2076	46.1870058	212,935	396	66	135
Croatia	CRO	1998	145	14	2420	1931	45.0804728	21,851	489	72	137
England	ENG	1908	119	16	2428	1919	54.1238716	50,346	464	80	96
Netherlands	NED	2427	139	17	2450	2037	52.1008080	16,039	409	82	74
Czech Rep.	CZE	4612	250	18	2419	2060	49.7334107	30,440	351	84	54
Germany	GER	16774	945	18	2508	2197	51.1069790	137,854	311	67	102
Slovakia	SVK	2117	110	19	2326	1866	48.7054718	18,932	460	88	68
Spain	ESP	13960	646	22	2468	2076	40.2444863	194,897	393	72	110
Italy	ITA	5520	212	26	2382	1898	42.7966357	116,318	483	75	120
	M	4282	399	11	2406	2009	47.0146260	354,661	393	73	104
	Sd	4845	500	6	90	157	5.9531910	1,331,103	84	9	34

Country Distances

There were two types of measures to determine distances (*w*) among the 24 countries, geographical latitude, and country size. Geographical latitude for each country was obtained from country centroids in decimal degrees (DD) as provided in the `rgeos` and `rworldmap` R-packages (Bivand & Rundel, 2019; R Core Team, 2019; South, 2011). The country size in square miles was obtained from Encyclopædia Britannica, Inc. (Editors, 2022). Both types of measures were determined by two squared matrices containing the absolute differences in geographical latitudes and country sizes, respectively, among the 24 countries and zeroes in the main diagonals. These were the weight matrices for the autocorrelation analyses with the RED measures.

Statistical Analyses

We analyzed the spatial autocorrelation structure of RED with both the global and local Moran's *I* index (Moran, 1948). This index characterizes either the positive or the negative correlation of a variable with itself across a finite set of well-defined spatial locations. The global Moran's *I* index is determined by multiplying the centered variable respect to its mean for two distinct spatial locations as shown in (1) and (2),

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_{i=1}^{n} (x_i - \bar{x})^2} \qquad (1)$$

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \qquad (2)$$

In these equations, w_{ij} is a matrix of spatial weights with zeroes in the diagonal, for $i, j = 1, \ldots, n$, with n observations (n = 24 countries), and x_i is the spatial variable for location i usually given in row-standardized form where each weight is divided by the total sum of its corresponding row, and then given $s_0 = n$. The local Moran's I as shown in (3), informs about the local spatial structure of each observation with respect to its neighboring observations, assuming a standardized value (z) of the observed variable (Anselin, 1995).

$$I_i = \frac{n z_i \sum_{j=1}^{n} w_{ij} z_j}{\sum_{i=1}^{n} z^2{}_i} \qquad (3)$$

The local Moran's I indices for each country were computed assuming a standardized form of the variable under analysis, with positive I values indicating similarities across spatial locations in the target variable, and negative I values indicating dissimilarity across spatial locations in the target variable.

The statistical significance of the global and local Moran's I was evaluated with a Monte Carlo approach (Anselin, 1995; Serlin, 2000). In this Monte Carlo procedure, the null sampling distribution of a given variable was obtained by simulating the variables of interest (RED) several times under the null hypothesis to generate their corresponding empirical distribution. Each empirical distribution was subsequently compared with the resulting statistic of interest. In our case and under the null hypothesis of spatial randomness, this procedure was based on randomly permuting the observed values in the RED scores over the fixed spatial locations, assuming the initial weight matrix (w), and the null hypothesis of spatial independence of each of the variables under analysis (RED).

This resulted in a random attribute spatial distribution based on a permutation procedure, where each variable was randomly placed over the fixed locations. An approximate test to assess the goodness of fit of the proposed model (i.e., null hypothesis) was therefore obtained by computing the rank of the resulting empirical measures of the spatial autocorrelation in this null sampling distribution based on m random permutations. The critical value of this test with α significance level was the $100 \times (1 - \alpha)$th percentile. Hence, the null hypothesis was accepted when an observed empirical autocorrelation was equal or smaller than this critical value. This approach generated a pseudo p-value used to assess the statistical significance of the targeted spatial autocorrelation measure. Specifically, this simulation approach was based on 999 null sampling distributions, which is a sufficient number of replications to obtain the empirical distribution of this variable under the null hypothesis.

Results

Figure 2 shows the Pearson correlation among the RED measures. While the raw (R) and expected measures (E) were unrelated ($r = 0.09$, $p = 0.6809$), there was a robust positive correlation between the raw (R) and the curve difference (D) measures ($r = 0.49$, $p = 0.0162$), and even a stronger negative correlation between the expected (E) and the discrepancy (D) measure ($r = -0.81$, $p = 1.592\text{e-}06$). In this latter plot, smaller countries clustered at the bottom right quadrant (England, Azerbaijan, Lithuania, Netherlands, Slovakia, Hungary, Slovenia, Czech Republic, and Georgia), whereas larger countries clustered at the top left quadrant (Russia, Turkey, Ukraine, France, Spain, Germany, and Poland). Hence, larger countries had lower expected (E) differences but higher discrepancies (D), whereas smaller countries had higher expected (E) differences but lower discrepancies (D) between both curves.

Table 2 shows the global Moran's I when addressing country latitude and country size (excluding Russia). Of the three analyzed variables (RED), only the expected measure (E) that contemplated the impact of differential participation rates of males and females, yielded a statistically significant negative value (-0.1160, $p = 0.0470$) concerning country size. This negative value essentially suggested dissimilarities in this specific measure (E) across countries regarding their size. These outcomes suggest in addition that for raw (R) and discrepancy (D) measures, the spatial structure in terms of these measures was independent of geographical latitude and country size.

Table 3 shows the local Moran's *I* findings in the expected (E) measure, with countries ordered by increasing country size. The countries for which the local Moran's indices yielded statistically significant values are shown in boldface. Positive *I* values indicate similarities, whereas negative *I* values indicate dissimilarities in E. As can be seen, countries with significant values, either with positive or negative *Is*, were either small or large concerning country size. Indeed, the *p*-values associated with the Moran's *I* tend to be small for smaller countries up to a certain country size (i.e., from Slovenia to Greece). For the eight smallest countries with $p \leq 0.05$, shown in boldface, there were only two countries with negative values (Netherlands and Azerbaijan) indicating that they differed in E compared with their neighboring countries regarding country size. The positive values in the remaining six countries (Slovenia, Croatia, Lithuania, Serbia, Bulgaria, and Greece) suggested remarkable similarities in the E measure. For the largest countries (Spain, France, Ukraine, and Turkey), however, the negative *I* values highlight that there were dissimilarities rather than similarities in the E measure.

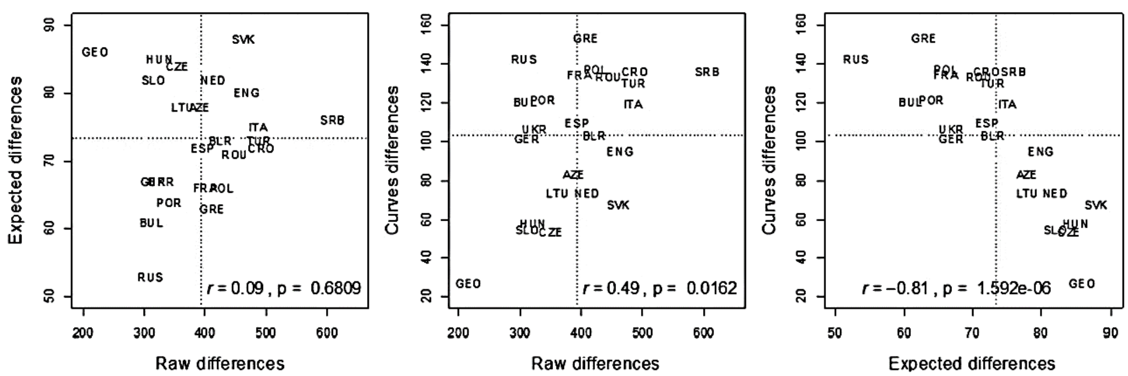

Figure 2. Pearson correlations among the three types of sex differences (RED: Raw, Expected, and Discrepancy measures) in chess expertise (points are represented by country acronyms as shown in Table 1).

Table 2. Global Moran's *I* under geographical latitude and country size in raw (R), expected (E), and discrepancy (D) measures of sex differences in chess expertise.

	R		E		D	
Condition	*I*	*p*	*I*	*p*	*I*	*p*
Latitude	-0.0642	.1812	-0.0337	.4645	-0.0507	.2763
Size*	-0.0199	.2893	-0.1160	**.0470**	-0.0541	.2633

Note. Russia was removed from the analysis with size because of its being an outlier.

Table 3. Local Moran's *I* under country size in the expected (E) measure. Countries are ordered by increasing size (Sq. Miles)

Country		Size (Sq. Miles)	E	*I*	*p*	M:F
Slovenia	**SLO**	**7827**	**71**	**12762.51**	**0.0320**	**7**
Netherlands	**NED**	**16039**	**82**	**-30022.64**	**0.0400**	**17**
Slovakia	SVK	18932	88	-53180.65	0.0571	19
Croatia	**CRO**	**21851**	**72**	**8773.42**	**0.0200**	**14**
Lithuania	**LTU**	**25212**	**73**	**4866.88**	**0.0370**	**4**
Georgia	GEO	26911	86	-43227.17	0.0571	2
Czech Rep	CZE	30440	84	-34551.08	0.0561	18
Azerbaijan	**AZE**	**33436**	**78**	**-12600.24**	**0.0490**	**3**
Serbia	**SRB**	**34116**	**64**	**34734.94**	**0.0270**	**12**
Portugal	POR	35603	76	-5610.09	0.0521	12
Hungary	HUN	35920	85	-35236.23	0.0881	12
Bulgaria	**BUL**	**42823**	**66**	**23934.65**	**0.0390**	**6**
England	ENG	50346	80	-14367.12	0.1091	16
Greece	**GRE**	**50944**	**63**	**28136.46**	**0.0501**	**8**
Belarus	BLR	80155	78	-4904.81	0.1812	4
Romania	ROU	91699	82	-6209.41	0.3694	7
Italy	ITA	116318	75	399.59	0.2973	26
Poland	POL	120725	61	-10990.23	0.4935	6
Germany	GER	137854	67	-10791.72	0.1682	18
Spain	**ESP**	**194897**	**72**	**-7026.47**	**0.0160**	**22**
France	**FRA**	**212935**	**66**	**-28954.36**	**0.0410**	**13**
Ukraine	**UKR**	**233090**	**67**	**-27284.89**	**0.0350**	**7**
Turkey	**TUR**	**300948**	**73**	**-5037.83**	**0.0170**	**10**

Moreover, Figure 3 shows that the small countries with statistically significant positive Moran *I* values were indeed geographically close except for Lithuania. Apart from being similar size, Slovenia, Croatia, Serbia, Bulgaria, and Greece, share geographical borders, a consistent linguistic background, and comparable climatic circumstances derived from their similar latitude within a 39 (Greece) and 46 (Slovenia) range of latitude degrees, and vicinity to the Mediterranean Sea.

Figure 4(a) shows the relationship between country size and the Moran's *I*, highlighting the negative values (i.e., dissimilarities) of the four largest countries (Spain, France, Ukraine, and Turkey), and of the two small countries (Netherlands and Azerbaijan). Figure 4(b) shows that for the smallest countries a robust inverted U-shaped relationship emerged between the local Moran's *I* and the respective country male to female ratio (M:F). These outcomes indicate that there were dissimilarities in the E measure of sex differences in chess expertise for countries with extreme M:F ratios (Azerbaijan = 3 and Netherlands = 17), while there were similarities for the six countries with more balanced M:F ratios (Slovenia, Croatia, Lithuania, Serbia, Bulgaria, and Greece).

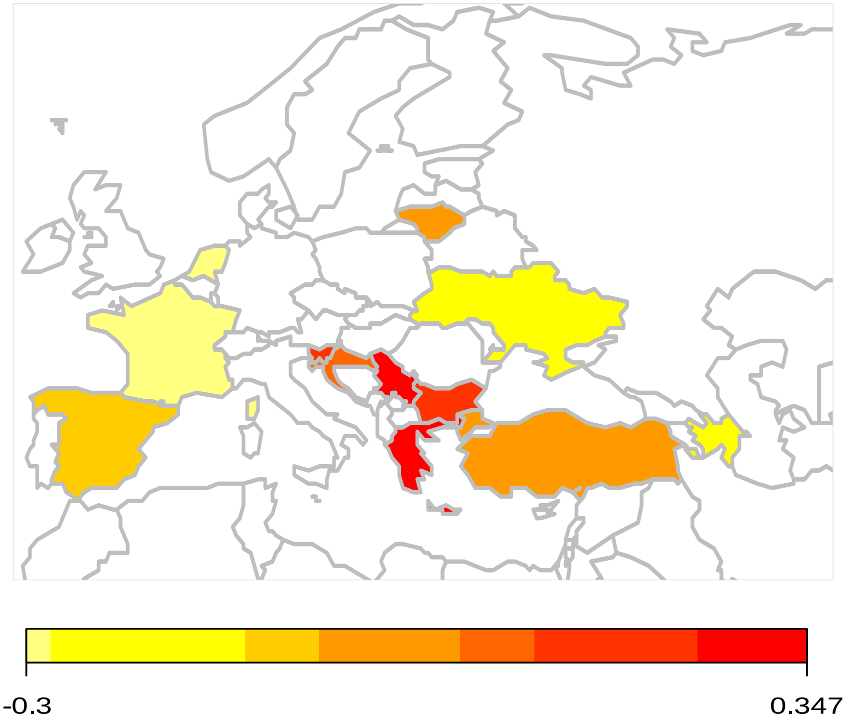

Figure 3. Local Moran *I* for eight small countries (Slovenia, Netherlands, Croatia, Lithuania, Azerbaijan, Serbia, Bulgaria, and Greece), and four large countries (Spain, France, Ukraine, and Turkey). The actual Moran's I were divided by a factor of 10^5 to ease the plot reading.

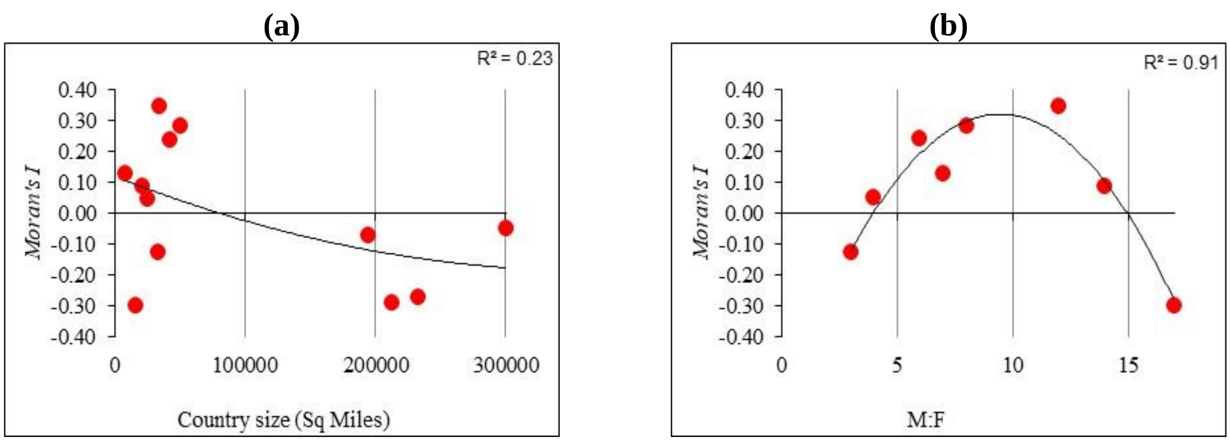

Figure 4. (a) Relationship of local Moran's *I* with country size; (b) Relationship of local Moran's *I* with male to female ratio (M:F). The actual Moran's *I* were divided by a factor of 10^5 to ease the plot reading.

Discussion

Whether sex differences in chess expertise depend on the disparity in the number of males and females or on other biological and cultural factors is a contentious topic in the light of extant mixed findings (Bilalic & McLeod, 2007; Bilalic et al., 2009; Blanch, 2016; Blanch et al., 2015; Chabris & Glickman, 2006; Charness & Gerchak, 1996; Howard, 2005, 2014a, 2014b; Knapp, 2010). Nonetheless, perhaps the gist of this controversy is to be found by asking why, among chess experts across countries, meaningfully lower numbers of females than males predominate. The underrepresentation of females in chess resembles the underrepresentation in science, technology, engineering, and mathematics (STEM), and in executive and politics related professions (Wai, 2013; Wai et al., 2010). Males also outnumber females in uneven career choices and life priorities, surprisingly even when there are sex similarities in ability (Benbow et al., 2000; Lubinski et al., 2014).

From this viewpoint, it could be argued that males outperform females in chess because of a complex mixture between discrepant male to female ratios, psychobiological sex differences, and social and cultural factors. Specific geographical factors have been largely unexplored. This study addressed this issue with past outcomes about sex differences in chess expertise evaluated across 24 countries in Eurasia (Blanch, 2016). Three types of measures tapping the sex gap in chess expertise (raw, expected, and discrepancy, RED) were contrasted against country latitude and country size. These contrasts were undertaken from both global and local perspectives. That is, evaluating the 24 countries as a whole and also considering the relationship of each country with its neighboring countries in terms of latitude and size.

The main findings suggested that there were some global differences and similarities regarding country size in the (E) measure only, but not regarding country latitude in any of the three evaluated measures. This E measure calibrates the raw sex differences in chess expertise that are explained by the discrepancy in the number of male and female participants in each country. Twelve countries at the local level showed both differences and similarities in (E) that varied with country size. There were four large countries with a range between 194,897 and 300,948 square miles (Spain, France, Ukraine, and Turkey), and eight smaller countries with a range between 7,827 and 50,944 square miles (Slovenia, Netherlands, Croatia, Lithuania, Azerbaijan, Serbia, Bulgaria, and Greece). Similarities prevailed among smaller countries, whereas differences emerged among the largest countries.

The local Moran's *I* outcomes from the four larger countries suggested differences in the E measure, with France and Ukraine showing lower E measures, 66 and 67, respectively, and Spain and Turkey showing somewhat higher E measures, 72 and 73, respectively. In contrast, the eight smaller countries were more similar in the E measure, except for Azerbaijan and the Netherlands, which held the lower (3) and higher (17) male to female ratios, respectively. Except for Lithuania, the countries showing similarities in the E measure share geographical borders by being fully interconnected, from West to East: Slovenia → Croatia → Serbia → Bulgaria → Greece. Moreover, they share a similar language background, cultural and historical attributes, and climatic environmental circumstances because of their proximity to the Mediterranean Sea.

While it remains unclear how and why the variability in such factors might influence the ubiquitous sex gap in chess expertise, the findings from the current study shed additional light about sex differences in chess expertise when considering geographical characteristics. The current outcomes showed that a reduced group of similar countries in terms of geographical location and cultural background yielded a very similar indicator (E) of the sex gap in chess expertise (Slovenia, Croatia, Serbia, Bulgaria, and Greece). Therefore, geographical distal factors appear of some relevance in considering further research about the persistent sex gap in chess expertise, particularly when undertaking comparative studies across different cultures. As suggested elsewhere (Rothwell et al., 2018), a form of life stemming in geographical, historical, and socio-cultural conditions may impinge on the quality of performance and styles in sports. For instance, the case has been made regarding a smaller sex gap in chess expertise in Georgia (Howard, 2014a, 2014b), a nation that appears to be specially encouraging chess playing among females and that shows lower sex gaps when compared with other countries. Moreover, some geographical and climatic characteristics have been recently related with individual differences in behavior that might be potentially important for chess performance, such as creativity, aggressiveness, or individualism (Van de Vliert & Van Lange, 2019).

This set of distal conditions and background circumstances could therefore modulate the differential involvement and performance of males and females in the chess domain. Indeed, some of these countries held large D measures that were above 100 points (Bulgaria, Greece, Serbia, and Croatia), a discrepancy highlighting that factors other than participation rates could be potentially valid to explain the sex gap in chess expertise. The underlying mechanisms relating these factors with actual chess expertise, however, remain unknown albeit apparently deserving of further research efforts.

There are several limitations worth noting about the present study. The current findings were constrained to a single point in time, the March 2014 Elo rating list (FIDE), and to a rather reduced amount of 24 countries with a notable constraint in the range of country latitude. Future studies applying spatial analyses or other available methods could be easily extended to the evaluation of eventual changes in the sex gap in chess expertise over time (Blanch, 2018; Howard, 2012), and to more countries with a larger variation in geographical latitude and country size. Furthermore, using a single point for each country to characterize its location with respect to the rest of countries is an obvious oversimplification to analyze the data with the Moran's *I* index, which describes the spatial autocorrelation structure of a variable that changes among nearby locations in space. These locations represent areas where the given spatial variable is assumed as constant inside each of these areas. Hence, assuming a single point to characterize the spatial location reinforces the idea that the variable of interest is constant for a given area, while allowing to conceive this single location as a correct simplification of the whole area (i.e., country). Moreover, there are additional geographical characteristics that could be evaluated such as climatic and temperature factors (Van Lange et al., 2017), or human capital related factors such as broad political, economic, and social outcomes associated with human development (Stoet & Geary, 2015).

Geographical factors have been generally ignored when studying differences in behavioral processes, and in the specific search for plausible explanations about the prevalent sex gap in chess expertise. The findings in this study highlight that systematic spatial patterns arising in the comparison of different countries and cultures can contribute to explain in part the persistent sex differences in chess expertise.

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Authors' Declarations

The authors declare that there are no personal or financial conflicts of interest regarding the research in this article.

The authors declare that they conducted the research reported in this article in accordance with the Ethical Principles of the *Journal of Expertise.*

The authors declare that they are not able to make the dataset publicly available but are able to provide it upon request.

ORCID iDs

Angel Blanch
http://orcid.org/0000-0002-6578-944X

Carles Comas
http://orcid.org/0000-0003-4432-865X

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