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Article

How to improve at chess: Uncovering insights using regression analysis

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SUMMARY

Chess is an intellectually challenging game which has grown in popularity recently. The game benefits young players by improving cognitive and problem-solving skills, memory, concentration, and math/reading skills. It also benefits older players by slowing down mental decline. Since chess is centuries old, there exists a lot of advice, rooted in conventional wisdom, for improving performance. For advanced beginners (players with International Chess Federation ratings between 1,500 to 1,700), such advice advocates for aggressive practice techniques either in breadth or depth of play. Specifically, five factors characterize these techniques: 1) number of daily games played, 2) the proportion of higher-rated opponents played, 3) the number of unique openings played, 4) the number of unique opponents played and 5) the extent to which players resign and lose games. We hypothesized that advanced beginners would improve faster at chess when they follow these aggressive practice techniques. We tested these factors using a data set comprised of 162,000+ games played by 1,250+ players on the Lichess platform over a six-month period. We used the difference in rating points as a proxy for improvement and used simple and multiple linear regression analyses. Our analysis showed that such techniques had a mixed impact on individuals' ratings. Specifically, playing more daily games, playing more higher-rated opponents, and losing through fewer resignations were inversely related to improvement. Conversely, having greater depth through fewer unique openings seemed to help, while the number of unique opponents was not a significant factor. Coaches and players can use these findings to tailor their practice programs with a more balanced approach.

INTRODUCTION

Chess is a centuries-old game that tests the mental acumen of humans, both in terms of strategy and tactics of the game, as well as the psychological aspects of competing. It requires high levels of concentration, patience, pattern recognition, and mental speed to calculate a series of moves and outmaneuver the opponent (1,2). Chess is a competitive game, played at amateur, state, national and international levels (3). Learning how to play chess has many benefits, especially for children (4). Studies have shown that playing chess improves children's cognitive and academic skills, problem-solving skills, improves their memory, and has positive effects on math and reading (5,6). Among the elderly, studies have shown that playing chess slows mental decline (7). During the COVID-19 pandemic, chess saw a rise in popularity that has continued post-pandemic with more tournaments established to capitalize on this interest (e.g. Chess World Cup expansion, Freestyle Chess Greatest of All Time (G.O.A.T.) Challenge and Chess 9LX tournament) (3,8). The rules of chess are very well-defined and logical. The players face off on a board with 64 black and white squares placed alternately. Each player has 16 pieces – one player plays white pieces, while the other plays black. There are six unique types of pieces, all which have unique mechanics in game play (1,2). The players take turns alternately to move, threaten, or take an opponent's piece, and create traps or protections (1,2). The main goal of a chess game is to checkmate the opponent's king, which means to corner to king in a way that the king has no safe square to move to, or no other protection (1,2). Victory can also be achieved if the opponent resigns, or if they run out of time. The game can also end in a draw or stalemate, when neither player can win or lose (1,2).

Depending on the positions of the pieces on the board, there are several different lines of play, each being a series of moves that can possibly unfold (1,2). Players periodically calculate these lines and evaluate their current game strength based on how favorable the current position is. The calculations can run very deep, with expert players (grandmasters) being able to see 10-15 moves ahead, and sometimes more (9,10). Computer-based chess engines are a great tool to help analyze such complex lines, for improvement. Given the vast number of combinations of moves possible, it is unfeasible for players to account for all possible scenarios throughout the game (11). They have to combine intuition with raw calculative power, especially given the time constraints of any game. These time constraints are caused by a clock put on each player that causes instant loss if the player lets their time run out (2). So, while chess has a strong logic-based component, the sheer number of possible games is estimated to be higher than the total number of atoms in the universe (9). Thus, there is an art and science to winning a game of chess.

When chess is played competitively, players get a rating (12,13). This rating is meant to reflect the strength of a player and how well they play chess. There are a few different systems of ratings, differing based on countries and international standards (12,13). In U.S., the US Chess Federation (USCF) maintains a USCF rating of its registered players which range from 100 to above 2,500, while the main international body, International Chess Federation (FIDE), maintains its own ratings for players worldwide (12,13). These are called FIDE ratings and range from 1,000 to above 2,500. Each chess federation employs a specific formula to calculate the ratings, which is a function of the player's current rating, the rating of the opponent, and the outcome of the game, to name a few (12,13).

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There is much conventional wisdom (traditional recommendations from chess coaches) that has developed on how to improve a player's game and increase their ratings (14-19). There are chess books on the theory of openings and endgames, and chess puzzles and exercises, and online resources such as artificial intelligence (AI) engines that help analyze games and recommend the "best moves" from a given position on the board (9,10,20-22). To the best of our knowledge, no one has researched this hypothesis and its related factors that are rooted in conventional wisdom.

We restricted the focus of our study to advanced beginner players that have FIDE ratings between 1,500 and 1,700, since we wanted to provide insights for players who are serious about pursuing chess, and those who are most likely to benefit from this research. We hypothesized that, based on conventional wisdom, pursuing aggressive practice techniques either in breadth or depth of play, would lead to faster improvement in chess. Conventional wisdom advocates that by playing greater number of games daily, playing a greater proportion of higher-rated opponents, going deeper into fewer number of unique openings, playing a greater number of unique opponents, and continuing to battle on the board with fewer resignations would all lead to faster improvements in chess.

We used publicly available data from Lichess.org, a major online chess platform, and focused on classical chess, since it is considered the traditional type that most people are familiar with. Classical chess is also the primary game type played for world championships games. We used statistical methods such as simple and multiple linear regression to determine which of the above factors are significant in improving a player's rating over a six-month period. We found that playing more daily games, playing more higher-rated opponents, and losing through fewer resignations were inversely related to improvement in chess, while playing fewer unique openings seemed to help a player improve faster. Additionally, the number of unique opponents was not a significant factor affecting improvement at chess. This indicates that more is not always better for chess practice techniques. Players can balance their practice plans on the quantity of games played, types of opponents (higher or lower rated), while pursuing more in-depth study of a few openings, when they are at the advanced beginner stage in their chess careers.

RESULTS

We collected game data from Lichess.org on 1,256 advanced beginner players who had played classical games for six months from July 2023 – Dec 2023. Lichess maintains an extensive free database of player and game information that allowed us to track individual player performances, as measured by the change in their online ratings over a period of time. We chose a six-month period that provided a long enough timeframe to study player progress while keeping the data size manageable. We processed this data further to derive information about average number of daily games played, percentage of higher-rated opponents played, the number of unique openings played (normalized for the number of games), the number of unique opponents played (normalized for the number of games), and the percentage of losses that ended with a resignation by the player (as compared to a checkmate, or being out of time). We further tracked how each of those factors related to a change in the player's online rating (the increase or decrease in this rating over six months as representative of the improvement or decline in strength of a player's chess game). The starting rating of a player has a strong influence on the manner in which their rating points increase or decrease, which we controlled for by exclusively focusing on the 1,500-1,700 rating range. This rating range represents the advanced beginner levels of players. Simple linear regression models were used to determine the relationship based on individual factors, and multiple linear regression models were used to validate those relationships, while determining statistical significance of those factors.

Our initial results were based on simple linear regression. We found that the number of games played daily (on average) had a negative correlation with a player's rating change (slope = -5.42, R^2 = 0.002, **Figure 1**). This suggested that the greater the number of daily games played, the lower the rating increase was, which was contrary to our hypothesis. We

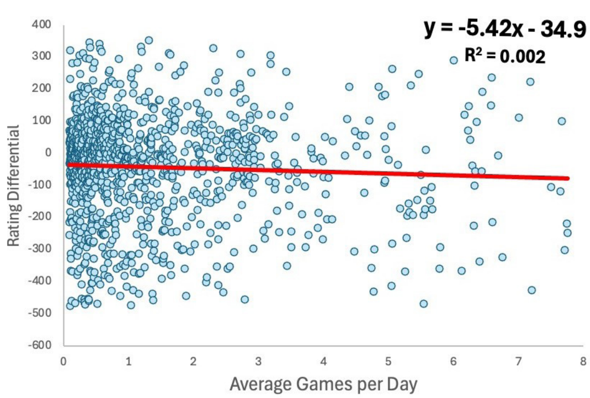

Figure 1: Negative association between average daily games played and change in player ratings. Change in player ratings over six months relative to average daily games played during that time. Average number of daily games is calculated as total number of games divided by duration, where "duration" is calculated as the difference between the last date and first date of play during the 6-month timeframe. Simple linear regression was carried out (slope = -5.42, R^2 = 0.002).

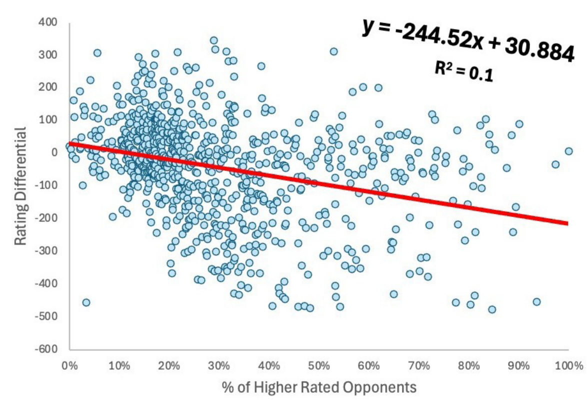

Figure 2: Negative association between percentage of higher-rated opponents and change in player ratings. Change in player ratings over six months relative to percentage of higher-rated opponents played. Higher-rated opponents are defined as opponents who are higher than the player by more than 50 rating points. The percentage value is calculated as (total number of higher-rated opponents divided by total number of games played). Simple linear regression was used (slope = -244.52, R^2 = 0.1).

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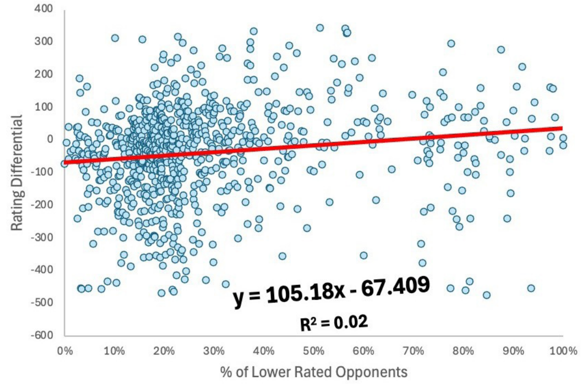

Figure 3: Positive association between percentage of lower-rated opponents and change in player ratings. Change in player ratings over six months relative to percentage of lower-rated opponents played. Lower-rated opponents are defined as opponents who are lower than the player by more than 50 rating points. The percentage value is calculated as (total number of lower-rated opponents divided by total number of games played). Simple linear regression was used (slope = 105.18, R^2 = 0.02).

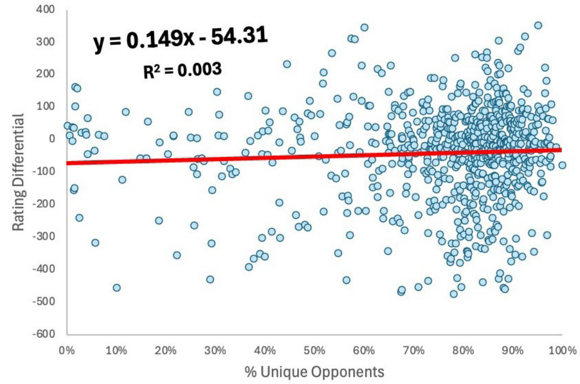

Figure 5: Slightly positive association between percentage of unique opponents and change in player ratings. Change in player ratings over six months relative to percentage of unique opponents played. Unique opponents are derived on a per-player basis. The percentage value is calculated as (total number unique opponents divided by total number of games played) so as to normalize for games played by a player. Simple linear regression was used (slope = 0.149, R^2 = 0.003).

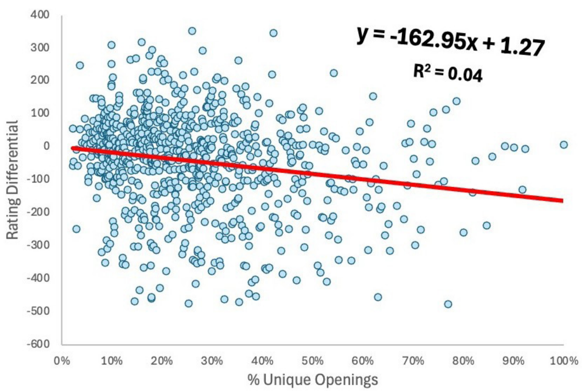

Figure 4: Negative association between percentage of unique openings played and change in player ratings. Change in player ratings over six months relative to percentage of unique openings played. Unique openings are derived directly from the Lichess data. The percentage value is calculated as (total number unique openings played divided by total number of games played) so as to normalize for games played. Simple linear regression was used (slope = -162.95, R^2 = 0.04).

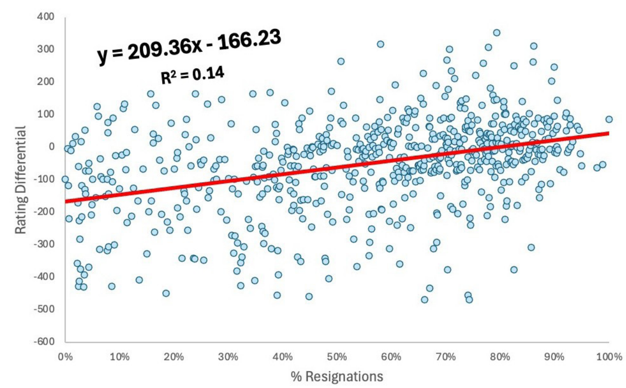

Figure 6: Positive association between percentage of losses ending with resignations and change in player ratings. Change in player ratings over six months relative to percentage of resignations by the player in their losses. Number of resignations are directly derived from the Lichess data. The percentage value is calculated as (total number of resignations divided by total number games lost) so as to normalize for games lost by the player. Simple linear regression was used (slope = 209.36, R^2 = 0.14).

also found that playing a greater percentage of higher-rated players was inversely related with a rating increase (slope = -244.52, R^2 = 0.1, **Figure 2**). Conversely, playing a greater percentage of lower-rated players was positively related with a rating increase (slope = 105.18, R^2 = 0.02, **Figure 3**). These results were also contrary to our hypothesis. Additionally, playing fewer unique openings was associated with greater gains in ratings (slope = -162.95, R^2 = 0.04, **Figure 4**). This supported our hypothesis. The number of unique opponents that a player plays against showed a negligible increase in a player's rating change (slope = 0.15, R^2 = 0.003, **Figure 5**). This suggested some support for our hypothesis. We found that the percentage of losses that ended with resignations (instead of checkmates or running out of time) increased as the player's rating change increased (slope = 209.36, R^2 = 0.14, **Figure 6**). This is contrary to our hypothesis.

We further validated our results with multiple linear regression model, to determine the statistical significance of the above factors, and eliminate the possibility that individual factors were masking the effect of other combination of factors in our simple linear regression models.

For multiple linear regression, we found that four out of the five factors were statistically significant **(Table 1)**. The average number of daily games played (p-value = 0.017), percentage of higher-rated opponents played (p-value < 0.001), number of unique openings played (p-value < 0.001), and percentage of losses that ended with resignations (p-value < 0.001) were all statistically significant **(Table 1)**. The number of unique opponents was statistically insignificant (p-value = 0.355) **(Table 1)**. The overall R^2 value for our multiple linear regression model was 0.17 **(Table 1)**.

Since the number of unique opponents was not a significant factor, we repeated our multiple linear regression analysis after removing that factor. We confirmed that the other four factors were indeed statistically significant **(Table 2)**. These four significant factors, along with the starting rating

Regression Statistics						
Multiple R	0.42	Adjusted R-Squared	0.17	Observations	1256	
R-squared	0.17	Standard Error	154.68			
Model Summary						
	Coeff	Std. Err	tStat	P-value	Lower 95%	Upper 95%
Intercept (constant value added to model)	-338.0	127.05	-2.66	7.91E-03	-587.25	-88.74
Rating at start of 6-month period	0.17	0.08	2.10	3.60E-02	0.01	0.32
Percentage of higher-rated opponents	-149.4	28.96	-5.16	2.89E-07	-206.23	-92.58
Percentage of lower-rated opponents	142.3	31.17	4.56	5.53E-06	81.1	203.40
Number of unique openings played	-120.8	28.59	-4.22	2.57E-05	-176.85	-64.68
Average number of games played daily	-8.0	3.34	-2.38	1.74E-02	-14.49	-1.40
Percentage of losses with resignations	143.8	17.05	8.44	8.84E-17	110.38	177.26
Number of unique opponents	24.3	26.28	0.92	3.55E-01	-27.25	75.86

Table 1: Regression model output with independent variables representing all five factors that are part of our hypothesis, and their statistical significance for predicting rating change (over 6 months). Significant factors (p-value < 0.05) are marked in green, while insignificant factors are marked in orange.

Regression Statistics						
Multiple R	0.42	Adjusted R-Squared	0.17	Observations	1256	
R-squared	0.17	Standard Error	154.67			
Model Summary						
	Coeff	Std. Err	tStat	P-value	Lower 95%	Upper 95%
Intercept (constant value added to model)	-313.9	124.35	-2.52	1.17E-02	-557.87	-69.96
Rating at start of 6-month period	0.16	0.08	2.07	3.88E-02	0.01	0.32
Percentage of higher-rated opponents	-155.2	28.28	-5.49	4.94E-08	-210.66	-99.70
Percentage of lower-rated opponents	136.0	30.42	4.47	8.55E-06	76.29	195.65
Number of unique openings played	-114.4	27.74	-4.12	3.98E-05	-168.77	-59.95
Average number of games played daily	-8.5	3.28	-2.59	9.67E-03	-14.94	-2.07
Percentage of losses with resignations	145.9	16.89	8.64	1.72E-17	112.78	179.06

Table 2: Second regression model with independent variables that are statistically significant factors (p-value < 0.05), after removing insignificant predictors. The multiple linear regression was improved by eliminating the only insignificant predictor (number of unique opponents).

of a player, accounted for an R-squared value of 0.17 **(Table 2)**. This reflected the percentage of explained variance in the player's rating change over six months.

DISCUSSION

Our analysis yielded mixed results. Compared to our hypothesis, our results showed an inverse relationship for three of the five factors; one factor was statistically insignificant, and one factor was supported in keeping with the hypothesis. We believe there are different reasons for each result.

The first factor in our hypothesis implies that playing more games daily will give a chess player good practice and give more opportunities to improve one's game (15,18). However, there is a negative relationship between rating change and average number of games played **(Figure 1)**. This is further validated by the negative coefficient associated with this factor in the final multiple linear regression model **(Table 2)**. This could be due to a few different reasons. One possibility is the mental fatigue of playing too many games. Another is a phenomenon known as "going on a tilt." This occurs when a player starts losing multiple games, and in an attempt to regain lost rating points, they play more games only to lose more games (14). This suggests playing more than a few games per day might be counterproductive, but further research is needed to identify the optimal number of games for a player. Coaches can use this finding to create awareness amongst their students about the drawbacks of playing too many games in a single day.

For the second factor, playing a greater percentage of higher rated opponents, the result was also counterintuitive. Coaches usually recommend playing higher rated players for two reasons – first, the player is tested against a higher-quality player and gets exposure to a better level of play, and second, the player will gain a lot of points if they win (15). In the event that the player loses the game, they will lose very few points, since they are the underdog to start with, and the outcome is consistent with the expected result. However, the data shows a negative correlation when playing higher-rated players and a positive correlation when playing lower-rated players **(Figure 2, 3)**. This may be because of the low probability of winning against a higher-rated player, and therefore, the expected value of a rating gain versus a rating loss. With this new information, coaches can advise their students to play lower rated opponents as well, though further research is needed to identify the optimal mix of lower and higher rated players that advanced beginner players should try to target.

For the third factor, playing fewer number of unique openings, coaches typically advise advanced beginner students to learn one opening for white and one opening for black (15). Our analysis shows that playing fewer unique openings helps improve one's rating positively, when the player is of advanced beginner strength (FIDE ratings between 1,500-1,700). At that stage, it is more beneficial to have depth of knowledge in a few openings, than to spread one's knowledge thin on many openings. Knowing the various lines of play at increased depth, for a single opening can help a player navigate better not just at the start of the game but also in middle game and can prove to be an advantage. As the player moves to higher ratings and becomes an advanced player, this strategy may change.

For the fourth factor, playing a greater number of unique opponents, players expect that they would benefit more since there is a greater "pool of rating points" from which their rating increases can draw from, if the player wins. Our results show a slight positive correlation, underscoring this thinking **(Figure 5)**. However, our model does not show number of unique opponents as a statistically significant factor (p-value = 0.355, **Table 1**). Intuitively, this can be explained if we consider that an opponent's game and level of play is also changing over the same six months. So, in essence, the same opponent is playing like a different player. However, both players could get familiar with each other's playing styles, so it would not be entirely as if playing a new opponent – it is a different situation. Therefore, it is hard to really get a true comparison of few opponents versus many opponents.

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The fifth factor captures a typical advice of coaches to not give up easily through resignations, but to keep fighting (17,19). Lost positions can be saved, and opponents can blunder moves (19). However, we found that players with a higher percentage of resignations (relative to losses), saw a greater increase in their ratings. This is a seemingly counterintuitive result. However, we think this may be because as players get better (and their rating points increase), they are able to calculate deeper lines and see more clearly if they are winning or losing. A higher percentage of resigns could just be reflective of a stronger player's understanding of likely loss for them, compared to those players that get checkmated. Furthermore, after resigning from a game, players can have more time at their disposal to start on a new game where they have a better chance of winning with a fresh start. Losing with a resignation versus losing due to a checkmate does not cause a player to improve automatically. It is likely reverse causation – stronger players resign more because they see farther in a game and can determine an imminent loss. Coaches can use this insight when studying the long-term trends in their students' games. This may create awareness amongst coaches and players alike that an uptick in percentage of resignations in their games is not, by itself, a bad sign. This analysis is also limited in accounting for other confounding factors, such as not all resignations are a result of a pending loss.

We saw differences in outcomes based on a player's starting point, the player's rating at the beginning of the six-month period (i.e., starting rating). It is well-known that as a player's rating increases, it is significantly harder to improve their rating by a certain number of points, compared to a similar improvement when a player's rating is lower (23). This is because the competition is tougher, and so it is harder to stay consistent in one's performance as a player (23). We tackled this effect in two ways– first, by focusing on advanced beginner category of players, and second, by including the starting rating as a confounding variable in our regression analysis.

Our analysis has some limitations. Firstly, our study is based on data from Lichess.org for online games played by these players on that platform and does not have data of the players' over-the-board/in-person games, or other platforms the players may have used to improve their game play. This limits the ability to generalize these findings across platforms and modes of play. This also limits our ability to build a comprehensive model that can predict rating changes over time, as reflected by the low R-squared values in our models, though this was not the primary focus of our analysis. Additionally, we used ratings as a proxy for improvement in chess. While ratings do reflect improvement when they increase, players could be improving even if their ratings are not increasing. Rating increases are a function of who they play and how often they win. If they are playing progressively higher-rated opponents, improving at their game, but losing each time, ratings will not reflect the improvement. Another set of limitations for this study stem from being focused on advanced beginners. We have not analyzed how the findings might change if we focus on early beginners or advanced players. We believe these findings may change based on how advanced a player is, but this is part of future studies. Additionally, research can be done to develop these findings further, such as finding the optimal number of games advanced beginner players should play daily (on an average) to improve their ratings, or optimal mix of higher and lower rated opponents that a player can play against.

Players and coaches can use these findings in daily training by tailoring their practices with these factors in mind. For instance, players can limit the number of daily games played on an average, irrespective of the outcomes of prior games. Players can play a mix of higher-rated and lower-rated opponents, instead of focusing on only higher-rated opponents. By focusing on fewer unique openings, advanced beginners can focus on deeper understanding of those openings to help give them an advantage. Finally, players can benefit from understanding the limitations of using rating as a proxy for improvement. While it does reflect roughly the strength of a player, it may not always track improvements in a player's game. In short, improvement in chess for advanced beginners is not merely a function of playing more games or chasing stronger opponents, as per conventional wisdom – it is the result of deliberate structure in how players train, practice, and interpret their progress with the right context.

MATERIALS AND METHODS

The primary dataset used for this analysis was from Lichess.org (24). Lichess publishes a monthly database of all games played on the platform. A database was downloaded by us for the month of September 2023, and later for December 2023.

Python v3.10.4 through Jupyter Notebook was used as our primary programming platform to process the data and run the analysis (25,26). Within Python, we used zstandard and io libraries to decompress the data (25,27). 10,000 random classical chess players were extracted from those datasets, as a starting point. It was necessary to control for the starting rating of a player. So, for the random extraction, the data was filtered to obtain 10,000 players with FIDE ratings between 1,500 and 1,700 for that time frame. This ensured the analysis was focused on advanced beginner strength players. Bots, players with provisional ratings, closed accounts, and observations with null data were filtered out, leaving ~3,500 players for whom application programming interface (API) calls were made to get their six-month game history (from July 2023 – December 2023) (28). These were further refined to eliminate players that had less than ten games in six months and those that had played all their games in just one day. Finally, the dataset was filtered for outliers, leaving the dataset of players who were used in the analysis at 1,256.

Data wrangling and transformations involved denormalization of data and data flattening. The result was a combined dataset that had a user's game and rating history for six months and also had derived features such as percentage of higher-rated opponents played, duration for which a player was active during the six months, percentage of losses that occurred due to resignations. The data was exported to Excel to execute the simple and multiple linear regression models. Correlation coefficients were computed between the dependent variable (the six-month rating differential for a player) and the independent variables. Simple and multiple linear regression models were created to capture the statistical significance (or insignificance) of the five factors affecting our main hypothesis.

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