An Innovative Employment of Virtual Humans to Explore the Chess Personalities of Garry Kasparov and Other Class-A Players

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An Innovative Employment of Virtual Humans to Explore the Chess Personalities of Garry Kasparov and Other Class-A Players

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Abstract. Exploring chess players of different personalities, including the strengths and weaknesses of each remains an essential component in designing new chess applications. Research shows that virtual players play an essential role in helping researchers to explore chess personalities of different classes and playing styles. A virtual chess player is defined as a software simulation that mimics the playing style of a real chess player. The current study employs these players in investigating the personalities of three class-A players while competing against Garry Kasparov. Additionally, it examines the personality of Kasparov and how he performs while competing against the other class-A players. To this end, the study utilizes an experimental design to collect data from simulations of games between three class-A players against Kasparov. The class-A players range in their personalities: a player who prefers chess material, drawish, and a balanced player. The four players in the simulation are virtual humans that are programmed to represent real chess players. The findings reveal that the class-A chess players did not have the same performance. Likewise, the performance of Kasparov varied according to the opponent, although his opponents were from the same category.

Keywords: games, chess, personality, virtual humans, chess software, grandmasters, Kasparov

1 Introduction

Computer chess has attracted much attention over the years and it has been subjected to an extensive investigation by researchers from various disciplines. Recent years witnessed significant developments including computers and chess programs that are able to compete at a very high level and defeat top grandmasters. Nowadays, chess technology is very affordable and is widely used in training. Additionally, it offers many services, including the employment of virtual humans to enable chess players to train and compete against players of different skills and playing styles. For the purpose of this research, virtual chess humans are defined as software simulations that mimic real players including many world champions such as Kasparov and Polgar. These virtual humans make it flexible for a chess player to explore the playing styles of many other real players, ranging from beginners to top-rank grandmasters.

Each chess player, including virtual players, is described by two attributes: chess rating and chess personality. Chess rating is a numerical value assigned to each player depending on how he performs versus other opponents in the chess community — the higher the rating, the stronger the player [27, 30]. On the other hand, chess personality is a term utilized in previous HCI research, and it is defined as the perspective of a player during his chess games against other players of different styles [22]. For example, Kasparov's personality is characterized by his ability to make rapid calculations and explore innovative opening styles, which are the result of his extensive development [52]. He often offers piece sacrifices in order to allow his pieces to have extra flexibility to move over the chessboard. Kasparov was the world champion for more than twenty years, and he is considered the greatest player in history. This study investigates the personality of Kasparov by analyzing the games between Kasparov and three class-A players: Rand, Dobie, and Sunny. The three players vary in their chess personalities: Dobie is a player who prefers chess material, Sunny is a player who considers drawing games at an early stage, and Rand is a balanced player. The description of all the players employed in this research, including Kasparov, is offered by Ubisoft [52]. Additionally, the study examines the influences of Kasparov's personality on different class-A players. This study uses three measurements for chess personalities: number of moves in a game, error of a chess player, and the Chessmaster agreement percentage. All these measurements are obtained from analyzing the games in the study using the Ubisoft Chessmaster software.

The reason of choosing Kasparov in this study is that there is a growing body of literature that recognizes the importance of exploring his personality in chess [26, 28, 33, 37, 54]. His personality can play a significant role in addressing many issues in designing chess programs and understanding chess psychology. That is to say, analyzing the games between Kasparov and Deep Blue is still a primary concern for many researchers [11, 16, 38, 40, 51]. To the best of the researcher's knowledge, this is the first article exploring the personality of Kasparov while competing against other class-A players by the utilization of virtual humans. Additionally, the extensive literature review reveals only one study that explores chess personalities via the involvement of virtual humans [22]. Using virtual players to help in understanding chess personalities is crucial because of many reasons: It makes it easier for psychologists to use virtual humans as a tool to understand many aspects of games and their outcomes. Additionally, it can be used as a tool for helping medical students identify particular training techniques as research indicates the employment of tools with chess personalities in surgical training [47]. This research investigates the following questions:

– How does Kasparov perform against different class-A players who vary in their chess personalities?
– Is Kasparov making less or more errors when the personality of his opponent changes?
– How do the personalities of class-A opponents playing against Kasparov affect the length of the game?

– Do class-A players of various personalities perform differently while competing against Kasparov?

The remaining part of the paper proceeds as follows: Section 2 provides an overview of the related research in virtual humans, chess psychology, and personalities in HCI research; Section 3 describes the approach employed in this study; Section 4 outlines the results obtained from analyzing the games between the four virtual players; the findings are discussed in Section 5; Section 6 concludes the paper.

2 Related work

Virtual humans are increasingly playing vital roles in our daily lives. They are the outcome of the union of various disciplines such as psychology, human-computer interaction, gaming, and artificial intelligence. Researchers design them to serve in different domains such as medicine, tourism, instruction, and entertainment. Personality is an essential aspect of virtual humans. It has been a subject of many research studies exploring virtual humans in psychology and computer science. For example, Zibrek et al. [57] administered a research study to collect information on how virtual figures are perceived in virtual reality applications and whether their personality makes a difference or not. Their major finding was that the closeness towards virtual figures is described as a composite interplay between the appearance and personality. Similarly, Zhou et al. [56] presented virtual interviewers that communicate with users and judge their personality characteristics. Their study reported that the personality traits and interview context influence people to place trust in virtual humans.

Evidence from the literature suggests that chess is an attractive field to explore many questions about personalities, people, and societies [22, 34, 47]. A recent study by Dhou [22] explored different aspects of chess personalities from the perspective of virtual humans. In his work, he investigated the personalities of different virtual chess players and linked the findings to existing research in social sciences. Interestingly, the study shows that virtual chess players with identical ratings and different personalities can perform differently depending on their opponent. Additionally, he found that a grandmaster with an attacking style stimulates other less skilled players and causes them to make fewer mistakes as opposed to when they compete against a defensive grandmaster. This finding has roots in psychology, where people attempt to comprehend the difficult events in their lives when they take place [55]. What remains unknown is researching more chess personalities and how they are influenced by each other. Although it is possible to explore chess personalities by investigating real players, virtual chess players give a much greater flexibility in pairing players with different personalities, including world champions against less skilled players. Such flexibility is impractical, if not impossible with real human players.

Several attempts have been made to investigate the personalities of chess players. A classical work was conducted by de Groot [17] who examined players of different levels and attempted to explore the variations between experts and beginners. De Groot observed that chess experts could recall and reestablish meaningful chess patterns over the board as opposed to weaker players. Similarly, Chase and Simon [13] discovered that experts have faster recognition of chess patterns than chess beginners. Later, Vollstädt-Klein et al. [53] examined the personalities of advanced chess players and how they can affect chess performance. They found that female chess players were happier and had higher accomplishments than other females. On the other hand, their study reported that there was not a significant difference between the personality profiles of male players and non-players. Likewise, Stafford [49] employed an extensive database of games and discovered that female chess players exceed the expectations when they play against male chess players. For more studies investigating chess and gender, the reader is referred to [7, 9, 31, 32]. Dhou [19] classified chess applications into different categories and identified the best training approaches in each. Bilalić et al. [6] explored the personalities of children who play chess and their companions who do not. Their study revealed that children who scored higher in particular tests are more likely attracted to chess than their peers. Blanch [8] examined the top one hundred world champions and employed the domain latent curve model to investigate the personal differences. They found a strong association between age and tournament activity. Together these studies provide important insights into the psychology of chess players.

Although all these previous attempts investigated the personalities of chess players and how they perform in different settings, the topic of virtual chess players has still not yet been formally studied. The extensive literature review revealed that there is only one study that explored the personalities of virtual chess players [22]. The main advantage of employing virtual humans over real human players in understanding chess personalities is the flexibility in allowing players from different eras to compete against each other. For example, Dhou [22] investigated the variations between Leko and Anderssen who are grandmasters that exist in different periods. Another advantage of utilizing virtual players lies in the flexibility of designing a controlled experiment between a wide range of players of different skills. Interestingly, research showed that there is a strong correlation between certain moves made by humans and chess computers [36].

It is essential to note that current research recognizes the critical role played by personalities in HCI research. For example, Shohieb [48] developed a game that teaches children how to manage different disaster situations. Additionally, Sarsam and Al-Samarraie [46] introduced a user interface based on personality traits for mobile applications. Other studies investigated the issue of connecting the personality traits to the visual design favorites of users [1, 2, 45]. Caci et al. [12] explored the motives of Pokémon Game practice, personal variations linked with individual characteristics, and game attitudes. Bacos et al. [5] explored the influence of different personality traits on in-game personality demonstrative of counterfactual thinking. They found that personality relies on players' variations and their experiences of the game itself. In another study, McCreery and Krach [39] investigated the causes of why people appear aggressive in an online setting and explored different types of aggression.

They found that proactive aggression was prophesied via agreeableness, extraversion, and emotional stability, while the reactive aggression was prognosticated via agreeableness and emotional stability. More research explored online learning environments and the students' feedback [4, 15]. The investigation of creatures' behavior is not limited to humans. It includes the behaviors of other creatures in different virtual environments such as biological reproduction, ants, and ecological systems [3, 18, 21, 23, 41]. Many of these studies are aimed at reducing the size of binary data that is widely used in text and other formats [20, 24, 25, 44].

To summarize, although psychologists and computer scientists have frequently emphasized virtual humans in different applications, there is only one study investigating their role in understanding chess personalities [22]. This article investigates the personalities of Kasparov and three class-A players to explore how a player from a particular class can be influenced when he competes against a player from another class.

3 Method

3.1 Participants

This study investigates four virtual chess players: three class-A players and Kasparov. The class-A players have different chess personalities, as follows:

- Dobie: He somewhat goes for chess material while competing against other players.
- Rand: He is a balanced chess player and characterized by a profound proficiency in chess openings.
- Sunny: She is not competitive and attempts to draw her games from the beginning. Additionally, she is known for controlling the center, but sometimes ignores the pawn structure.

The three class-A players have almost identical USCF ratings. The USCF ratings of Dobie, Rand, and Sunny are 2118, 2113, and 2115, respectively. In this study, the three class-A players play against Garry Kasparov, who makes rapid calculations and considers creative openings. In addition, Kasparov sometimes chooses neglected opening styles such as Evans Gambit. It is important to emphasize that the four players employed in the current study are virtual humans that mimic real chess players.

3.2 Materials

The present design involves two independent variables:

- IV1: The color of Kasparov's pieces. In this study, each opponent played half of the games with White and the other half with Black.
- IV2: The personality of Kasparov's class-A opponent. This independent variable has three levels: a player who prefers material, a drawish, and a balanced player.

The researcher utilized the Chessmaster developed by Ubisoft to analyze all the chess games in the study [52]. To this end, the researcher considers measurements of five dependent variables generated by the Chessmaster, as follows:

- DV1: The total number of moves
- DV2: The total error of moves played by Kasparov
- DV3: The total error of moves played by a class-A player
- DV4: The Chessmaster's agreement percentage of Kasparov's moves
- DV5: The Chessmaster's agreement percentage of a class-A player's moves

The total error is a metric employed in calculating the errors made by different virtual players. It is calculated as the difference between the actual moves made by players and the optimal moves [14, 22]. The same metric was previously used in exploring virtual humans to understand the differences between chess personalities [22].

3.3 Procedure

In this research study, each class-A player played 98 games against Kasparov, half of them with white, and the other half with black. The researcher collected the data from all the games and analyzed it using the Chessmaster. The Chessmaster generated the five dependent variables for each game. The researcher used these dependent variables in exploring the personalities of the four virtual chess players employed in this study.

4 Results

The researcher analyzed the data in this study using a series of two-way ANOVA tests. Each dependent variable was submitted to a two color of Kasparov (White or Black) by three class-A player personality (drawish, prefers material, and balanced) two-way ANOVA. All the effects were reported as significant at $p < 0.05$.

4.1 Number of moves

The researcher conducted a series of two-way ANOVA tests to examine the effect of the class-A player's personality and Kasparov's color on each of the five dependent variables. There was a significant main effect of the class-A player, on the number of moves during the games, $F(2, 288) = 6.686$, $p = 0.001$. Paired samples t-tests show that there are statistically significant differences between the number of moves in the games played by different class-A players against Kasparov. There was a significant difference in the number of moves played by Rand ($M = 52.459$, $SD = 10.429$) and the number of moves played by Sunny ($M = 58.888$, $SD = 17.684$); $t(97) = 2.844$, $p = 0.005$. Similarly, there was a significant difference in the number of moves played by Sunny ($M = 58.888$, $SD = 17.684$) and the number of moves played by Dobbie ($M = 51.622$, $SD = 16.358$); $t(97) = 2.968$, $p = 0.004$.

4.2 Kasparov's total error

There was a significant main effect of the class-A player, on the total error of Kasparov during his games, $F(2, 288) = 3.108$, $p = 0.046$. A paired samples t-test reveals a significant difference in the total error of Kasparov when he competes against Sunny ($M = 2.245$, $SD = 3.197$) and when he competes against Dobbie ($M = 1.290$, $SD = 2.412$); $t(97) = 2.349$, $p = 0.021$.

4.3 Class-A player's total error

There are no significant effects.

4.4 Chessmaster's agreement percentage on Kasparov's moves

The interaction between Kasparov's color and the player is significant, $F(2, 288) = 3.262$, $p = 0.04$ (Figure 1). To break down this interaction, the researcher conducted a series of paired samples t-tests. Paired samples t-tests show that when Kasparov plays with Black, there are significant differences between the Chessmaster's agreement percentages on his moves when he competes against Dobie ($M = 97.204$, $SD = 2.041$) and Rand ($M = 96.081$, $SD = 3.054$); $t(48) = 2.092$, $p = 0.042$; and when he competes against Sunny ($M = 95.694$, $SD = 2.823$) and Dobbie ($M = 97.204$, $SD = 2.041$); $t(48) = 2.931$, $p = 0.005$.

4.5 Chessmaster's agreement percentage on class-A players' moves

There was a significant main effect of the class-A player on the chessmaster's agreement percentage on the moves made by class-A players, $F(2, 288) = 7.791$, $p = 0.001$. Further paired samples t-tests show that on average, the Chessmaster agrees more on the moves made by Sunny ($M = 88.704$, $SD = 4.878$) than Rand ($M = 86.418$, $SD = 4.957$); $t(97) = 3.143$, $p = 0.002$, and on the moves made by Sunny ($M = 88.704$, $SD = 4.878$) than Dobie ($M = 85.939$, $SD = 5.779$); $t(97) = 3.628$, $p < 0.001$.

5 General discussion

The purpose of the current research study was to explore the psychology of competition between Kasparov and three class-A players. To this end, the researcher designed a study consisting of four virtual chess players: Kasparov and three other class-A players. In the current experiment, the researcher examined different dependent variables that measure the lengths of the games and the performance of the involved virtual players.

The experimental results showed that Kasparov tends to make more mistakes when he plays against Sunny (drawish) as opposed to playing against Dobie (prefers material). These findings are consistent with

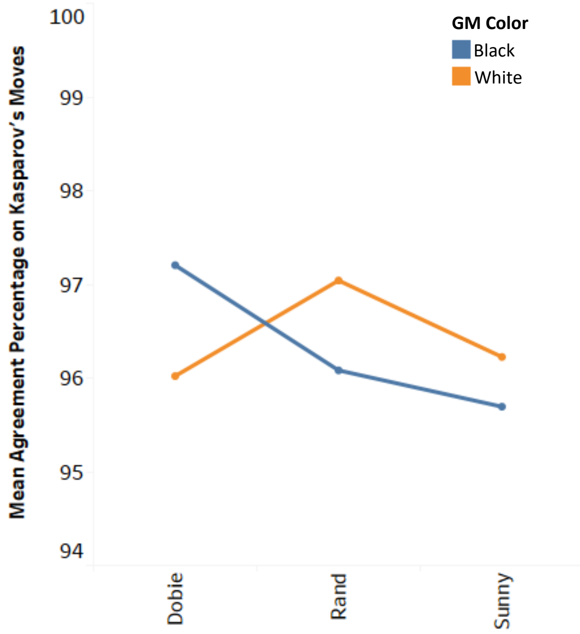

Fig. 1. The mean values of the Chessmaster's agreement percentage on Kasparov's moves. Except for Dobie, the Chessmaster agrees more on Kasparov's moves when he plays with the White color.

the outcomes from the previous study [22] investigating the errors made by grandmasters while playing against other class-B players. The study in [22] showed that grandmasters performed differently while playing against different players from the same class. A possible explanation is that Sunny has a good control of the center of the game. That is to say, although she neglects the pawn structure, Kasparov's total error was higher when he competes with her as opposed to competing with Dobie. Her strength is evidenced by the chess literature revealing that controlling the center is more important than having effective pawn combinations [35]. Additionally, one of the standard powerful fundamental postulates in chess is that a strong side attack requires a solid center, which increases the chances of attack [10]. Kasparov did better when Sunny accepted the Queen's Gambit (Figure 2). The variation of accepting the Queen's Gambit sounds like a favorite direction for Kasparov, and that is probably why he performed better as opposed to the other variation of declining the Gambit. It is essential to mention that Kasparov does well in the opening phase and his game against Deep Blue reveals that the computer could not outplay him during the opening [42].

Controlling the center did not only influence the total error of Kasparov, but it also affected the moves in the games. The paired samples t-tests showed that Sunny was the most resisting player, and the games

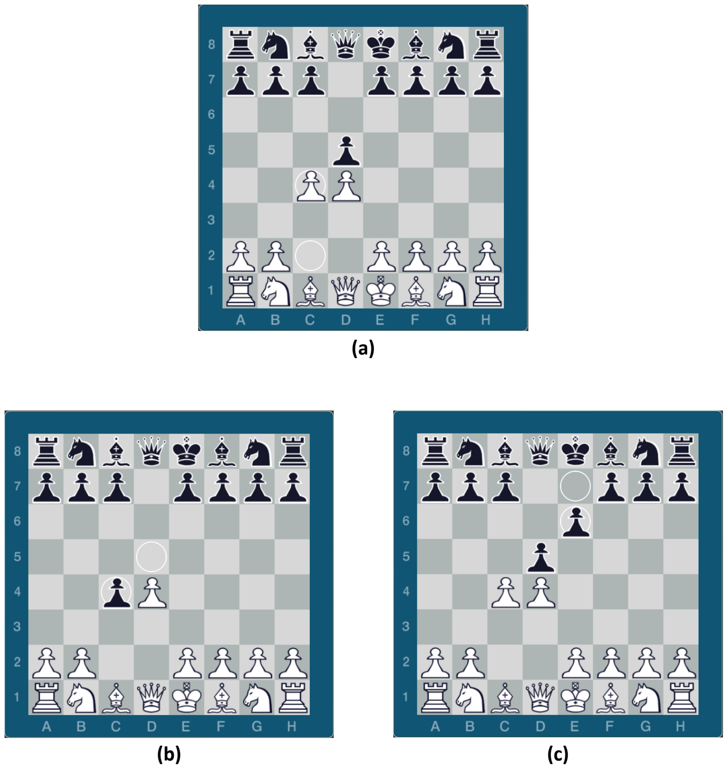

Fig. 2. An example showing two variations of the Queen's Gambit. In the two games, Kasparov plays with White and Sunny plays with Black. In (a) Kasparov offers a pawn sacrifice; (b) Sunny decides to choose the accepted Gambit variation that allows Kasparov to control the center; In (b) Sunny decides to decline the Gambit. The results from two games showed that Kasparov made fewer errors and took a greater advantage when Sunny accepted the Queen's Gambit

against her were the most extended in the simulation. Additionally, analyzing two games showed that giving up the center by accepting the Queen's Gambit allowed Kasparov to gain more advantage as opposed to Sunny declining the Gambit. More research is needed to investigate the effects of declining the Gambit. Interestingly, previous research shows a strong relationship between the chess center principle and management. Flamholtz [29] used this principle in his analogy, describing centralized and decentralized management. Another explanation of why Kasparov did better when Sunny accepted the Gambit is probably because of the opening style. In other words, the opening phase determines the direction of the game, and each player has his preferences. For example, when Sunny accepted the Queen's Gambit in one game, the total error of Kasparov was 0, while it was 6.04 when she declined the Gambit. The pawn sacrifice is often offered by Kasparov so that he can get additional mobility to his chess pieces.

The results showing that Kasparov did better when Sunny accepted the Queen's Gambit are consistent with other findings revealing the importance of the opening phase. The opening determines the flow of the game and might even cause a player to lose. For instance, Deep Thought defeated Karpov in the opening and the initial stage of the middle game and had many circumstances to draw the game [43, p. 197]. Different grandamsters and research studies have noted the importance of openings in chess. For example, Michael Adams emphasizes the importance of the opening and believes that working on it is more applicable than working on other phases of the game [50]. Interestingly, in the previous study, the findings showed that a player who is good at the opening did better than a balanced player, although they belong to the same category [22]. Additionally, Levene [36] showed the importance of the opening books as part of chess engines. Chess applications are connected to large databases that contain different openings and their variations.

6 Conclusion

The present study was designed to determine the effect of the personality of chess players on the outcomes of their games against different opponents. To this end, the study involves designing an experiment consisting of four virtual chess players: one grandmaster, and three class-A players. The selected virtual grandmaster was Garry Kasparov, and the three class-A players varied in their personalities. One of the more significant findings to emerge from this study is that Kasparov performed differently while competing with the other class-A players. Additionally, Kasparov did better when the other player followed his line of play (i.e., Accepted Queen's Gambit). Similarly, the three class-A players performed differently although they had the same opponent, Kasparov.

These findings suggest that in general players can behave differently depending on their opponent even if they are within the same class. Additionally, the present findings are consistent with the previous outcomes in [22], showing the differences between players from the same class with different personalities. Furthermore, class-A players performed differently when they were competing with Kasparov, although they have almost identical ratings. The outcomes from this research can help understand the ratings of chess games between players of different personalities and ratings. That is to say, this study paves the way for further research that explores the influence of different chess personalities on each other to investigate new techniques for chess training based on opponents. For example, in the study in [22], the findings showed that less skilled players performed better while competing against an aggressive grandmaster as opposed to a defensive player. Similarly, the current study revealed that the software agrees more on the moves made by a player who controls the center of the game. Such findings reinforce the chess concept that stresses on the importance of controlling the center. Additionally, they can be used as guidelines for chess players to recommend individual personalities for chess training, showing that chess rating is not the only factor to select an opponent for training and personality is also another significant factor.

This research has many practical applications. For example, it helps in designing new chess programs that take the chess personality into consideration and suggest opponents depending on the personality of the player. In other words, some players perform better while competing against certain players, and it would help to suggest different opponents from which they can probably learn the most. Second, further understanding of the chess personalities allows designing new experiments that can probably reveal new findings about social aspects. For example, the study in [22] revealed many interesting findings that are linked to social sciences. In general, therefore, it seems that virtual chess players can contribute to social sciences and prove useful in understanding human behavior.

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