

# Supporting Online Game Players by the Visualization of Personalities and Skills Based on in-Game Statistics

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**Abstract:** Although the COVID-19 pandemic has increased people demanding to play online cooperative games with others, in-game random team matching has not fully supported it. Furthermore, toxic behaviors such as verbal abuse and trolling by randomly gathered team members adversely affect user experience. Public Discord servers and game-specific team matching services are often used to support this problem from outside the game. However, in both services, players can obtain only a few lines of other players' self-introductions before playing together, and therefore their anxiety about possible mismatches is a major obstacle to the use of these services. In this paper, we aim to support team matching in an online cooperative game from both aspects of players' personalities and skills. Especially, we perform team member recommendation based on the visualization of in-game statistical information by computing players' personalities and skills from their game masteries and character preferences in a typical game called VALORANT.


## 1 INTRODUCTION

Today's online video games are widely played as cooperative games in which players cooperate with others regardless of whether the type of game is player-versus-environment (PvE) or player-versus-player (PvP). In PvE, several players cooperate to progress through the game; in PvP, teams consisting of several players usually play against each other. Such a game often has a friend search feature that allows players to search for a player with a username, register the player as a friend, and play together. If it is not possible to prepare friends to play with in advance, the lack of team members is often filled by random matching. Although this random matching generally succeeds in matching players with similar skills (Corem, Brown, & Petralia, 2013), it does not sufficiently consider the compatibility between players. Rather, randomly matched members might not be able to cooperate due to the failure to divide roles, and sometimes they might exhibit troll behaviors such as intentional abuse and obstruction of

allies (Ho & McLeod, 2008) (Cook, Conijn, Schaafsma, & Antheunis, 2019) due to low relationships and high anonymity (Kwak, Blackburn, & Han, 2015). Although some games implement the function for the same players to play together continuously, it is rarely used due to the experience mentioned above and the unknown background of the players. Although the COVID-19 pandemic calls for games as social spaces for people's interaction (King, Delfabbro, Billieux, & Potenza, 2020), a mechanism to support it within the game has not been sufficiently realized.

Discord<sup>3</sup> is software for communication with text chats and voice/video calls mainly on personal computers (PCs) and smartphones. It is characterized by the easy preparation of a small server for a few people as well as a large-scale community server for thousands of people. A large-scale server is often open to the public, and people who participate in the server search for users with whom to play an online game together; while cooperating in an online game, they communicate via channels and individual calls within the Discord server. GameTree<sup>4</sup> is a matching

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<sup>4</sup> <https://gametree.me/>

service specialized in finding people to play games with. Users can search for other users to play with by registering their simple attributes, the games that they often play, and their self-introductions. However, in both services, before users start playing together, the other users' displayed information is only a few lines of self-introductions, and their anxiety about possible mismatches is a major obstacle to the use of these services.

In this paper, we aim to support the matching of team members for an online cooperative game by using the two axes of personalities and skills. Based on in-game statistical information in a typical game called VALORANT, we perform team member recommendation based on the visualization of the information by computing players' personalities and skills from their game masteries and character preferences. We present the result of the experiment that we conducted to evaluate our method.

## 2 BACKGROUND

In this section, we describe the basics of VALORANT and Discord. First, we show the differences and similarities between VALORANT and other PvP online games, and explain how players find their friends. Next, we describe the role of Discord, how public Discord servers are used as a communication platform, and an example of a Discord server for VALORANT.

### 2.1 VALORANT as a Cooperative Game

VALORANT is a 5-versus-5 cooperative character-based tactical first-person shooter video game being developed and published by Riot Games. According to unofficial statistical information (Active Player, 2022), the numbers of players of VALORANT are 22 million per month and 2.3 million per day, and the number of concurrent players at peak time exceeds 0.8 million people.

The main game modes are unrated and competitive, where the goal is to destroy enemies or to set or defuse bombs in the area. This rule is the mainstream of first-person shooter games, and a representative is the Counter-Strike series. On the other hand, the difference from most of the other games is that, in VALORANT, the characters used by players have their own characteristics. These characters can be classified into four roles (sentinels, controllers, duelist, and initiators). This feature is similar to that of Overwatch, a team-based action

game. In both games, players form a team with friends before the match begins, and basically divide their roles and fight together. Otherwise, players are randomly assigned to teams with other players of similar skill level for the game. It should be noted that when forming a team of 2 or 3 players in the competitive mode, players must have a rank difference of about  $\pm 1$  before they can line up in a match queue. Although a 4-player team is not allowed to play due to the game specifications, a 5-player team (called a fully premade team) is allowed to line up in the match queue regardless of the rank difference. However, the enemy team also must be a fully premade team.

### 2.2 Discord as a Communication Platform

Discord is a VoIP and instant messaging platform application. Millions of people send 4 billion messages through the Discord platform every day (Glen, 2022). Groups and communities in Discord are called servers. In this paper, the term "server" is used not to represent a central computer but to represent a community. Servers range from small ones consisting of closely related people to huge communities consisting of several thousand people.



Figure 1: User interface of a Discord server. The left side lists a part of the channels for text and voice communications. The central part presents self-introductions by users including their names, play styles and short messages.

Figure 1 shows an example of a medium-sized server (consisting of approximately 400 users) where we conducted the experiment presented in this paper. The server is further divided into channels that are displayed in a list as shown on the left side. Text channels are used for self-introductions, text chats, and discussions. In the voice channel, users in the server can freely enter and exit and directly communicate with each other by voice. On the right side of Figure 1, bot applications created by third parties are shown. Over 500,000 bot applications are used on Discord servers to help server customization, playing games, and keeping communities safe (Cap, 2022). We implemented our method as a bot application.

### 3 RELATED WORK

Delhove et al. showed that video game character preferences correlated with personality traits such as aggression and prosociality (Delhove & Greitemeyer, 2018). They focused on the class-based first-person shooter game *Overwatch*, in which 6-versus-6 players compete against each other. In their experiment, they used a large sample of game players ( $N = 2323$ ) to evaluate the relationship between players' in-game role preferences and personality traits. Preference for the aggressive role (i.e., attacker) was related to aggressive, non-prosocial personality types. On the other hand, this was observed only in self-reported measures, not in a small sample of objective playtime measures.

Corem et al. showed the relationship among player engagement, proficiency, and intrinsic motivation on a skill-based gaming platform (Corem, Brown, & Petralia, 2013). Their unique rating system matched players with similar proficiency levels. Competing with other players with a similar skill level improved the player's skill, which increased the player's satisfaction. This indicated that engagement increased when players felt that their playing was improving. Also, from the viewpoint of the game system, there was a trade-off between the speed of matching between players and the time to wait for players with similar abilities.

### 4 PILOT STUDY

As a pilot study, we verified the tendency of players' character preferences and the possibility of clustering. We looked at the data of 38 players searching for

friends on a public Discord server. Figure 2 shows the dendrogram of the result of clustering by the Euclidean distance and Ward's method, taking the number of times a character was selected. Since there are 4 roles of characters in VALORANT, the maximum number of clusters was 4, and the roles are colored differently. The yellow group was characterized by mainly the use of Chamber and Jett, aggressive characters fighting at the front. Both characters have the special skill of instantly leaving the current place. The purple group mainly used a character named Raze who used a special skill that took time to learn. These groups tend to be devoted to particular characters without using other characters. The red group, on the other hand, picked a wide range of characters. It can be considered that the users in this group selected characters according to other users or selected various characters according to their moods.

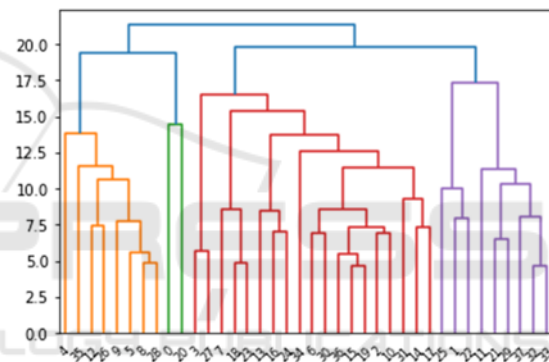


Figure 2: Dendrogram of the result of clustering character preferences in the pilot study by the Euclidean distance and Ward's method. The numbers along the horizontal axis indicate users.

### 5 PROPOSED METHOD

In this paper, we analyze the personalities and game skills of players based on in-game statistical information, and support team matching among players in a typical online cooperative game VALORANT. In the same way as the related work (Delhove & Greitemeyer, 2018), we use the tendency to select characters in the game as effective statistical information for personality analysis. There are currently 20 characters in the game, and they can be roughly divided into 4 roles. In our pilot study, we classified users into groups with 4 characteristics by clustering analysis. In the proposed method, we additionally use competition ranks that are certified in the competitive mode.

The proposed method is implemented as a Discord bot application. When a user gives in-game player ID to this application, it visualizes how they are positioned relatively to other users. According to the visualized information, the user interacts with other users by considering their personalities and competition ranks. Unlike previous research, this application enables quantitative analysis and visualization by the bot agent from in-game statistical information.

### 5.1 In-Game Statistics

In-game statistics are retrieved using the application programming interface (API) of Riot Games, the developer of VALORANT. We focus on characters as a feature of personalities and on competition ranks as a feature of players' game skills. The Discord bot application used in this proposed method applies these features to visualization. The application records the retrieved statistics in a database and utilizes them for later analysis.

### 5.2 Collecting Player Data

Information about the users of this bot application is recorded in the database, and it is also used for the users' visualization. To present users' information to the first users, we asked several people to tell us their in-game IDs and registered them in advance. For visualization, the VALORANT API and the Discord API are used to collect character preferences (a list of the numbers of times characters were selected), ranks of the competitive mode, VALORANT IDs, and Discord IDs.

### 5.3 Clustering Character Preferences

The users are clustered hierarchically based on the numbers of times they selected characters. We use the Euclidean distance to measure the distance between users and Ward's method to measure the distance between clusters. Based on 20 characters in the game, each user is represented as a vector  $u = (u_1, u_2, \dots, u_{20})$  whose components are the numbers of times the user selected characters.

### 5.4 Visualization by Dendrogram

Based on the clustering results and the users' competition ranks, a dendrogram that expresses both personalities and skills is generated, and is used to support the users in forming teams. Figure 3 shows a visualization by dendrogram. Clusters are colored by

using the threshold of 12 and the maximum number 4 of clusters. Based on related work (Delhove & Greitemeyer, 2018), we hypothesize that closeness on the dendrogram represents the personalities of users. The users know that closely positioned users have similar character preferences. It also means that distant users have different character preferences, and therefore they can be partners by complementing each other's role. In addition, the color of the username label is based on the rank of the competitive mode, giving the users playing the competitive mode a visual understanding of their game skills.

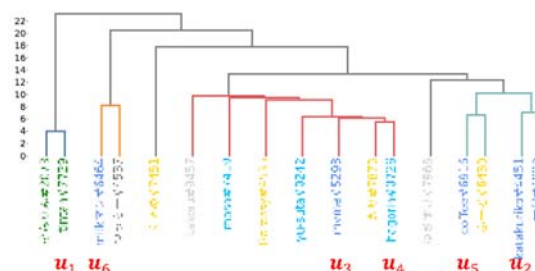


Figure 3: Visualization of personalities and skills by dendrogram.

## 6 IMPLEMENTATION

We implemented our Discord bot application by allowing users to interact with others through user-friendly slash commands (Nelly, 2021). This application is always running on a Heroku server, and is deployed on a public Discord server with 400 users who cooperated in our experiment. Any member of the server can use this bot by passing the in-game ID of VALORANT as an argument of the slash command on the channel where the use of this bot is permitted by the administrator.

When the system receives the in-game ID, it retrieves the user's most recent 86 matches by submitting the Production API Key to Riot Games. We use the data of the maximum of 20 matches excluding deathmatches. The application extracts the characters selected by the user and the rank of the competitive mode from the data. The data are linked with the user ID and stored in the Firestore database of Firebase. Finally, a dendrogram based on the recorded character preferences and competition ranks is generated and sent as a Discord embedded message as shown on the left side of Figure 4. The dendrogram is generated in real time using D3.js. The text of the embedded message contains a description of the visualization and a list of links to the profiles of the users. The page view that is opened with a link differs

between a PC and a smartphone: on the PC, the linked user profile is displayed on the browser as in the upper right of Figure 4; on the smartphone, the profile of the linked user is displayed in the application as in the lower right of the figure. In both, the user can send friend requests to other users.

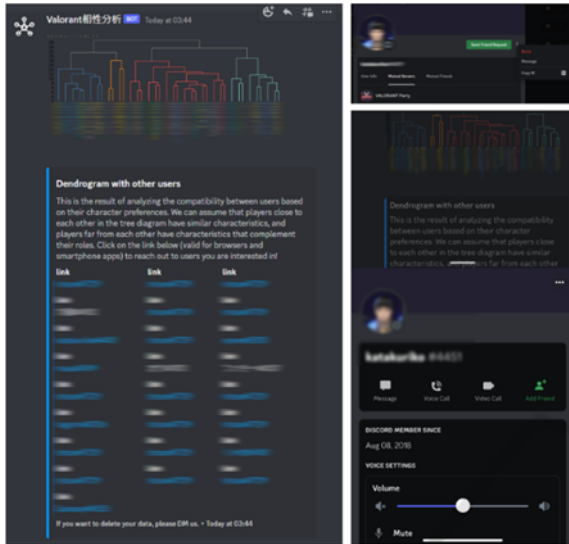


Figure 4: Screenshot on the left shows the dendrogram and its description sent to a user, where the links with blue letters indicate online users. The screenshots on the right show the different behavior of the bot application when a link is opened on a PC or a smartphone.

## 7 EXPERIMENT

We conducted an experiment to evaluate the proposed method. We first asked the administrator of an existing public Discord server to install our bot application. Next, we conducted two questionnaires with Likert scales: we asked the users of the Discord server to answer the first questionnaire immediately after using the bot application and also to answer the second questionnaire two or three weeks later. Our analysis is based on the statistics of the recorded data of the users and the results of the questionnaires.

### 7.1 Participants

The participants in the experiment were volunteer players (18-year or older) who had searched for VALORANT friends on public Discord servers. A public server named “VALORANT Party” cooperated in our experiments. A total of 16 participants (11 originally from this server and the other 5 from the groups known to them) used our bot

application. The first questionnaire was answered by 11 participants, and the second questionnaire was answered by 8 participants.

### 7.2 Procedure

The participants used the bot application and answered the two questionnaires at the two or three-week interval. The experiment was started by a slash command (Nelly, 2021) on the channel for the bot application that had been authorized by the server administrator. As shown in Figure 5, the slash command could be started from the suggestion list by entering a slash character in the text box for text chat. If a user entered his/her in-game ID separated into the name and the tagline, VALORANT statistics search using Riot API started. An edited reply showing the progress of the search was sent at any time, and one minute later, an embedded message with the visualization result as an embedded image was sent. It was left to the user whether to contact other users from the link in the message. As soon as the results were confirmed, the user was asked to answer the first questionnaire.

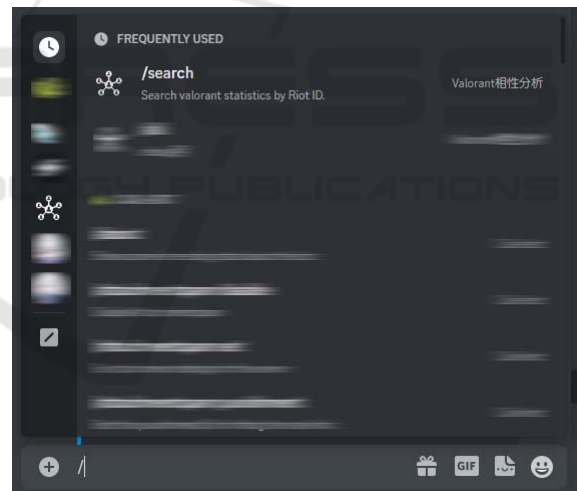


Figure 5: Suggestions that appear when a slash character is typed in the box at the bottom of the screen in a bot-enabled text channel.

Two or three weeks after the first day of the experiment, we asked the users to answer the second questionnaire. Based on the visualization results, we checked whether there were any changes. In addition, we asked the members of the pre-existing teams to evaluate each other, which was also examined by using the statistics.

### 7.3 Results of the Questionnaires

In the first questionnaire, we collected basic information such as the device used for the bot application and the experience of using public Discord servers. 29% of the participants answered that they had played with other users in the server. Although 70% of the users participated in the server, their use of the server was limited. Reasons for the limited use include “I still don’t know how to use the server” and “I found someone to play games with”. There were many cases where people joined the server but hesitated to talk to other users, or they did not need to find someone to play games with for some reason. Also, as shown in Table 1, 36.4% of the participants answered that they could not understand the visualization by dendrogram.

Table 1: Part of the result of the first questionnaire (%).

Question	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
I can get the meaning of the visualization	9.1	45.5	9.1	36.4	0.0
Competition ranks are important	9.1	45.5	9.1	27.3	9.1
I want to contact users via the displayed links	0.0	9.1	27.3	36.4	27.3

In the second questionnaire, we collected what the participants thought about personalities and skills. As shown in Table 2, 25% of the participants answered that their thought changed by the visualization results. On the other hand, more than half of the users answered that they found inconvenience about personalities and skills in both questions. The three users who did not care about the ranks in competitive mode were the members of the team of unrated players. The reason was that there was no difference in skills within the team, and that a full premade party could play the competition mode together regardless of the rank difference. Users’ interest in distance in the dendrogram was split evenly. The three users who were interested in closely positioned users adopted characters of all roles in the last 20 matches.

### 7.4 Mutual Evaluation Within a Pre-Existing Team

We present mutual evaluations and dendrograms of 6 users. Users  $u_1$  to  $u_6$  included in the dendrogram in Figure 3 were the members of a team that existed before the experiment. They played VALORANT’s unrated mode together at least once a week. We prepared a questionnaire with five questions shown in

Table 2: Result of the second questionnaire (%).

Question	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
My thought was changed by visualization results	0.0	25.0	25.0	37.5	12.5
Ranks were important in the competitive mode	12.5	50.0	0.0	0.0	37.5
Ranks were not important in the other mode	62.5	25.0	0.0	12.5	0.0
Inconvenience was caused by difference in skills	25.0	12.5	25.0	0.0	37.5
I am interested in users close to me	0.0	37.5	25.0	12.5	25.0
Inconvenience was caused by incompatibility of personalities	25.0	25.0	12.5	12.5	25.0

Table 3 for the 5 users other than  $u_1$  who was one of the authors, and asked them to evaluate the others in the team. Q1 and Q2 are about personalities, Q3 and Q4 are about roles in the game, and Q5 is about skills.

Table 3: Questionnaire for the mutual evaluation of team members.

Questions	
Q1	My personality and this user’s personality are distant
Q2	I often disagree with this user.
Q3	The roles that I and this user want to use are far.
Q4	The roles of mine and this user often work well after the game starts.
Q5	There is a difference between my skills and this user’s skills.

Q3 and Q4 about roles had many positive answers overall. This was because the team had already played many times and each member had a character to choose. For this reason, the roles in the game were divided and effectively handled. Regarding Q5, many users answered that they felt a difference between  $u_1$  and  $u_4$ , who usually played the competition mode.

Table 4 summarizes the results of Q1 and Q2 about personalities. The score for  $u_4$  was particularly high (4.25 out of 5). On the other hand, as shown in Figure 3, the clusters were rather close to the other users. In this way, individual cases cannot be judged only by general character preferences. Also,  $u_6$  was located further than other members on the dendrogram, but the similarity was not much different from those of the other users, showing intermediate values in the questionnaire. This was because the users grouped into the first cluster had outlier components that used extremely specific characters

(12 times out of 20). Since Ward's method has high classification sensitivity even for outliers, inappropriate clustering may occur as in this case.

Table 4: Average values for questions Q1 and Q2. Larger values indicate more different personalities. The row for each user  $u_i$  gives this user's evaluations of the other users. User  $u_1$ , who was one of the authors, did not evaluate the others.

User	$u_1$	$u_2$	$u_3$	$u_4$	$u_5$	$u_6$
$u_1$	-	-	-	-	-	-
$u_2$	2.0	-	1.5	3.5	1.5	1.5
$u_3$	2.5	2.5	-	3.5	2.0	2.0
$u_4$	3.5	2.5	3.5	-	2.5	3.0
$u_5$	3.0	3.5	2.0	5.0	-	3.0
$u_6$	3.5	3.0	2.5	5.0	2.5	-

## 8 DISCUSSION

Although we used character preferences and competition ranks as statistical information in the game, it is also possible to use other information such as the number of times a user played on each day of the week and weapon preferences. An effective indicator might be the account level of a player, which increases as the player plays the game. It is necessary to evaluate parameters from multiple perspectives such as subjective evaluation and machine learning to verify which statistical information is useful.

We assumed that users whose personalities were close based on their character preferences rarely conflict while users whose personalities are distant often conflict. We consider this from the viewpoints of personalities and game specifications. Regarding personalities, Lykourantzou et al. found that personality conflicts reduced team performance while balancing personalities significantly improved cooperative work performance (Lykourantzou, Antoniou, Naudet, & Dow, 2016). Regarding game specifications, online games such as VALORANT, in which multiple teams with multiple players compete, are usually designed to divide roles within teams. Since such a game currently organizes teams with several players, it can be played without problems even with similar roles. However, as the number of players in a team increases, the balance might become worse. From these two viewpoints, we can consider recommending players with different personalities instead of those with high similarities.

The percentage of the users who were not comfortable with the bot application and direct messages in Discord seems to be high. We asked 50

of the server members to cooperate in the experiment. 16 people used the bot application, 11 responded to the first questionnaire, and 8 responded to the second questionnaire. Although the bot application included a link to a document containing the terms and policies of the bot, we also used personal accounts to send messages about cooperation in the experiment. This was because many Discord servers including the server that we used in our experiment prohibited bot's direct messages.

Half of the participants in the experiment could not understand the dendrograms of visualization results. Most of the participants who could understand it had some background in computer science. Although information visualization has become a mainstream technology, understanding a visualization is not always easy for the people who see it (L'Yi, Chang, Shin, & Seo, 2019). Some of the answers for the questionnaires showed that the distances shown in the dendrogram were not clear to users. It is possible to extend the representation of the dendrogram not only with text descriptions, but also with animations, scaling, and opacity changes.

## 9 CONCLUSIONS AND FUTURE WORK

In this paper, we developed an application that visualizes personalities and skills of players based on the in-game statistics of the online game VALORANT. The distances of character preferences were close to the users' subjective evaluations, by which we were able to show the potential demand for visualizing personalities and skills of users.

Our future work will promote intuitive understanding of user relationships through scalable and interactive information visualization, and will support users to take the first step toward a new experience with other users. Although currently visualization results are embedded as images in Discord messages, our goal is to realize interactive visualization that runs in a browser. As the number of users grows, the visualization should be scaled by collapsing by clusters and filtering by ranks. We will also improve usability by effectively using user avatars, in-game icons, and statistical information in pop-ups. Visualization methods need to be validated based on construction tasks (L'Yi, Chang, Shin, & Seo, 2019). In-game statistics and experiments will also be used to analyze what parameters are effective as indicators of user relationships, including win rates and character combinations. Also, we will examine

the motivations of online game players to play with other players.

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