# Investigating the Relation between Playing Style and National Culture

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***Abstract*—In this study we examine playing styles in four popular Massively Multiplayer Online Games (MMOGs), namely *Battlefield 4*, *Counter-Strike*, *Dota 2*, and *Destiny*. We investigate to what extent national culture influences these playing styles, and whether players from countries with similar cultures exhibit similar playing styles as well. We gathered playing style information from hundreds of thousands of players of these games, and applied correlation and clustering algorithms to relate playing styles to nationalities and to Hofstede cultural dimensions. We found that playing styles are influenced by nationality and cultural dimensions, and that there are clear similarities between the playing styles of similar cultures. In particular, the Hofstede dimension "Individualism" explained most of the variance in playing styles between national cultures for the games that we examined.**

## I. Introduction

In video games, different players exhibit different playing styles. A playing style is a concise description of the general way in which a player behaves in a game. Many games support a large selection of playing styles to achieve the game's objectives [1], [2], [3]. Gaining an understanding of different playing styles used by players may help game designers to create games that are better suited to their player base.

Previous research showed that multiple player characteristics relate to in-game behavior [1], [2]. In the present article, we aim to determine whether one such characteristic, namely national culture, is related to a difference in playing styles, i.e., whether based on culture one can give an estimate of someone's playing style, and vice versa.

Hofstede [4] defined national culture as "the collective programming of the mind that distinguishes the members of one group or category of people from others." He defined six so-called "Hofstede dimensions," which represent different aspects of national culture. Hofstede found that different cultures can be distinguished based on these dimensions [5]. National culture is strongly related to multiple aspects of social behavior, such as motives, attitudes, norms and beliefs [6], [7].

In the domain of video games, earlier research into cultural differences between players mostly focused on differences in preferences rather than in-game behavior. Bialas et al. [8] addressed the relation between in-game behavior and national culture, using data from *Battlefield 3*. They grouped playing style variables into three categories, namely competitiveness, cooperation and tactical choices. They found differences between playing styles of different nationalities for the competitiveness and cooperation categories. However, they took only eight different countries into account, which were all "Western" countries. In contrast, in our research we use data from dozens of different countries from all over the world, including "non-Western" countries.

Moreover, most research in data analysis in video games focuses on only a single game (e.g., [2], [9], [10], [11]). As we aim to discover whether our results generalize over different games, in this research we investigate playing style data from four different video games, namely *Battlefield 4*, *Counter-Strike*, *Dota 2*, and *Destiny*. These four games were chosen because they are all multi-player games, for all of them we could build suitably large datasets, and all have a different approach to gameplay (as explained in section V).

We investigate the relationship between playing style and national culture in two ways, namely to find a relationship between playing style and (1) nationality, and (2) Hofstede's cultural dimensions.

The outline of this article is as follows: In section II we review related work. In section III we explain the concept of playing style. In section IV we explain the concept of national culture. In section V, we explain the datasets we generated for the four games used in the study. In section VI we explain our study implementation. In section VII we present our results. In section VIII we discuss our findings, and in section IX we summarize the outcome of this study.

## II. Related Work

Studies into playing styles approach the topic from different directions. Below we discuss three of these directions, namely (1) the differences between playing styles; (2) the relation between a player's personality and their playing style; and (3) the relationship between playing style and national culture.

Among others, differences in playing styles were studied by Eggert et al. [12]. They labeled playing style data from 708 players of the game *Dota 2*, and predicted nine player roles based on playing style. Liu et al. [13] showed that it was possible to identify a player based on their playing style in *StarCraft II*. They also predicted the player's next action based on their in-game behavior.

The relation between personality and playing style was studied by Yee and Ducheneaut [14], who used an online survey about personality and motivation to investigate players' in-game behavior. Van Lankveld et al. [1] measured the relation between players' behavior and the Five Factor Model of personality using questionnaires. Canossa, Martinez, and Togelius [15] investigated the correlation between players' motivational factors and their in-game behavior by analyzing *Minecraft* data. Bean and Groth-Marnat [16] studied the relation between player behavior in *World of Warcraft* and their personality via Big Five Factor Model.

There exist relations between culture and emotional expressions [17]. This fact is used in the research by Neesha et al. [18], which shows that players from different cultures understand emotions in video games differently.

The relation between national culture and playing style has been researched very little. That such a relationship exists is to be expected, as differences between members of different cultures are widely observed. How large the influence of national culture on playing style is, however, has been studied only sparingly [19], [20]. In this article, we investigate the relationship between national culture and playing style in more depth, and in particular aim to determine whether such relationships can be generalized.

## III. Playing Style

We define playing style as a set of features generated by a video game player's gaming behavior. Collections of features may be interpreted to reflect a more general playing style, e.g., "aggressive" or "exploratory." Depending on the game and the goals of the research, few or many playing styles may be distinguished. In principle, one could argue that every player exhibits their own playing style, but for the purposes of research and application, it makes more sense to distinguish playing styles in a more general way.

We are aware that the particular game that is used to study playing style has a strong influence on the kind of playing styles that can be observed. Different games offer different types of actions, different environments, different characters, and different tools. For instance, in *Destiny* players choose one of the main characters, who all function differently. What can be observed of a player is for a large part determined by the character that they play. As such, the character selection is part of the playing style.

## IV. National Culture

National culture concerns a set of cultural values, such as norms, behaviors, beliefs, and customs, which are common to the population of a nation. Naturally, nations may be close in their culture to each other, or quite distant from each other. A well-known framework to define national culture was given by Hofstede [5], [21]. A major competing framework is GLOBE (Global Leadership and Organizational Behavior Effectiveness) [22], but in our study we use the Hofstede dimensions as GLOBE is focused on the leadership in industries [23].

By means of replicated surveys concerning the values of people all over the world, Hofstede created six cultural dimensions based on statistical relationships. Each cultural dimension indicates a preference towards one state of affairs over another. Scores for each Hofstede dimension are available for more than 50 countries. Hofstede distinguishes the following six dimensions [21]:

- *Power Distance (PD)*. A high value for Power Distance indicates acceptance of a hierarchical order, a low value indicates that a society seeks an equal power distribution.
- *Individualism (IDV) vs. Collectivism*. The Individualism dimension is concerned with self-image, which is defined in terms of "I" (Individualism) or "we" (Collectivism).
- *Masculinity (MA) vs. Femininity*. The Masculinity dimension is concerned with a society's preference for values which are traditionally associated with males or females, such as achievement (masculine) or modesty (feminine).
- *Uncertainty Avoidance (UA)*. A high value for the Uncertainty Avoidance dimension indicates feeling threatened by uncertainty and trying to cope by avoiding unorthodox behavior. A low value indicates a relaxed attitude towards uncertainty.
- *Long-Term Orientation (LTO) vs. Short-Term Orientation*. Long-term orientation concentrates on thrift and future rewards, in contrast to short-term orientation, which appreciates traditions and fulfilling social obligations.
- *Indulgence (IDL) vs. Restraint*. An indulgent society puts great importance on personal happiness, whereas restrained societies are more prone to regulating positive emotions by strict norms.

The Hofstede dimensions have been used for game research before. They were, for instance, used to customize online gaming web sites [24], and to investigate the relation between national culture and players' experiences in MMOGs [25].

In our study, we did not pre-select the features which we surmise relate to the Hofstede dimensions. Instead, we built models based on all available features, and then examined the relationship between the strongest features and the Hofstede dimensions. Since all games that we study are team games, it is to be expected that many features relate in particular to the Individualism dimension, as players have the opportunity to express team-directed behavior vs. individualistic behavior.

## V. Data

In this section we describe the datasets created for each of the games used in the study: *Battlefield 4*, *Counter-Strike*, *Dota 2*, and *Destiny*.

### A. Battlefield 4

*Battlefield 4* is a First Person Shooter (FPS) game. The game enables many options for different strategies and tactics, both related to personal achievements and team support.

Statistics of *Battlefield 4* players can be acquired from the BF4stats website (bf4db.com/stats). It provides an API which can be called with a player's username and platform to retrieve statistics of the player. A web crawler was used to retrieve player names from the “general score” leaderboard on the website [19]. Subsequently, a second web crawler was built to retrieve playing style statistics for every player name. The crawler retrieved information on 158 features, such as kill/death ratio (KDR), objective scores, scores for different roles within the game, scores for different game modes, and the use of different weapons. Playing style statistics were retrieved for 119,834 players.

Only players who had played more than 24 hours total were taken into account, and only countries with 500 or more players were selected. To keep the dataset balanced, a random selection of 514 players from each country was taken (the maximum possible). The dataset used for the remainder of this article therefore consisted of 14,906 players from 29 countries.

### B. Counter-Strike

*Counter-Strike* is a FPS game, played with two competing teams. In this study we used *Counter-Strike: Global Offensive*. The game support different scenarios.

We used the Steam *Counter-Strike* API to retrieve *Counter-Strike* data [20] for 125,127 accounts. The data was retrieved in two parts: stats and achievements. The stats data contains 218 playing style features per player such as ‘total kills,’ ‘total deaths,’ and ‘total planted bombs.’ Each achievement feature represents one of the 167 possible in-game achievements, and indicates whether the achievement was acquired. We grouped the achievement data into five categories (team tactics, combat skills, weapon specialist, global expertise, and arms race and demolition) and transformed them into a ratio (the number of completed achievements by a player per category divided by the total number of achievements per category). We also grouped the weapon features into five categories.

We excluded players with less than 12 hours of total playing time. We also removed all countries with less than 500 players. Players from Belarus and Kazakhstan were removed from the dataset, because Hofstede cultural dimensions are not available for these countries. This left players from 26 different countries. To keep the dataset balanced, from each country a random sample of 537 players was taken (the maximum possible). Therefore, the final *Counter-Strike* dataset used for further analysis consists of 13,962 players.

### C. Dota 2

*Dota 2* (Defense of the Ancients) is a Multiplayer Online Battle Arena (MOBA) game, in which the player controls a single hero character (selected from 115 possibilities) in one of two teams, each team consisting of five players.

The *Dota 2* data was collected from Opendota (www.opendota.com/) via the Opendota API [20]. We selected a subset of the 232,326 *Dota 2* Steam accounts to gather data from, namely players which were active on Opendota and have a matchmaking rating (MMR) between 1,500 and 6,000 (thereby excluding very low and very high outliers). A total of 117,514 accounts met the criteria; we collected 78 *Dota 2* playing style features per player.

For the *Dota 2* dataset, only countries with at least 500 players were selected. Belarus, Kazakhstan, Myanmar, and Mongolia were excluded because their Hofstede cultural dimensions are not available. To keep the dataset balanced, from each of the remaining 30 countries we took a random sample of 512 players (the maximum possible).

### D. Destiny

*Destiny* is a FPS game with strong influences of Massively Multi-player Online Role-Playing Games (MMORPG). Players play in a small team against another small team, in one of 13 different game modes.

We collected players’ information from the DestinyTracker website (destinytracker.com) in September 2017. The dataset includes 94 playing style features of 11,637 players from 41 countries. The features include player skills such as Kill-Death ratio (KD), Kill-Death-Assist ratio (KDA), and kills per game; weapon features that show percentage of kills by different weapons; teamwork features such as number of revives that the player performed or received; and performance features such defensive kills and offensive, and average distance of kills.

Players with less than 24 hours total playing time were removed from the dataset. Countries with less than 250 players were also removed reducing the number of countries to 27. We decided not to balance the resulting dataset, considering that 250 players is relatively low, so we wanted to include more players for countries which have them. In the end, the dataset includes 8,240 players from 27 countries. For most countries the dataset contains between 250 and 300 players.

## VI. Study Implementation

This study is divided into four parts, of which the results are reported in section VII. First, in our datasets we look at variations in playing styles based on nationalities, using ANOVA tests. Second, we look at variations in playing styles based on Hofstede dimensions, again using ANOVA tests. Third, we look at how the playing styles of nationalities are related to each other using -Distributed Stochastic Neighbor Embedding (t-SNE) dimension reduction. Finally, we use machine learning models to predict nationality and national culture based on playing style.

In pre-processing the data, all time-dependent features (such as number of kills) were divided by the total playing time in minutes. Normalization was done by centering and scaling, i.e., by removing the mean of every feature and dividing every feature by its standard deviation.

All countries in the dataset were categorized into different groups based on their scores for each Hofstede dimension. Hofstede scores are specified in the range $[0, 100]$. We created four categories of scores for each dimension. Category 1 represents ‘low’ scores $[0, 24]$, category 2 represents ‘medium low’ scores $[25, 49]$, category 3 represents ‘medium high’ scores $[50, 74]$, and category 4 represents ‘high’ scores $[75, 100]$. An overview of these categorizations for the countries in our datasets is given in Table I. Naturally the numbers do not represent a full, inclusive view on a country’s national culture,

TABLE I: Categorization of countries based on their values for each Hofstede dimension.

| Country | code | PD | IDV | MA | UA | LTO | IDL | Dataset |
|---|---|---|---|---|---|---|---|---|
| Argentina | ar | 2 | 2 | 3 | 4 | 1 | 3 | CS, Dota |
| Austria | at | 1 | 3 | 4 | 3 | 3 | 3 | B4, CS, Dota, Destiny |
| Australia | au | 2 | 4 | 3 | 3 | 1 | 3 | B4, CS, Dota, Destiny |
| Belgium | be | 3 | 4 | 3 | 4 | 4 | 3 | B4 |
| Brazil | br | 3 | 2 | 2 | 4 | 2 | 3 | B4, CS, Dota, Destiny |
| Canada | ca | 2 | 4 | 3 | 2 | 2 | 3 | B4, CS, Dota, Destiny |
| China | cn | 4 | 1 | 3 | 2 | 4 | 1 | B4, CS, Dota |
| Czech Republic | cz | 3 | 3 | 3 | 3 | 3 | 2 | B4, CS, Dota |
| Germany | de | 2 | 3 | 3 | 3 | 4 | 2 | B4, CS, Dota |
| Denmark | dk | 1 | 3 | 1 | 1 | 2 | 3 | B4 |
| Finland | fi | 2 | 3 | 2 | 3 | 2 | 3 | B4, CS, Dota, Destiny |
| France | fr | 3 | 3 | 2 | 4 | 3 | 2 | B4, CS, Dota, Destiny |
| Hungary | hu | 2 | 4 | 4 | 4 | 3 | 2 | B4 |
| India | in | 4 | 2 | 3 | 2 | 3 | 2 | CS, Dota |
| Indonesia | id | 4 | 1 | 2 | 2 | 3 | 2 | CS, Dota |
| Italy | it | 3 | 4 | 3 | 4 | 3 | 2 | B4, CS, Dota, Destiny |
| Japan | jp | 1 | 2 | 4 | 4 | 4 | 2 | B4, CS, Dota, Destiny |
| Malaysia | my | 4 | 2 | 3 | 2 | 2 | 3 | CS, Dota |
| Mexico | mx | 4 | 2 | 3 | 4 | 1 | 4 | B4 |
| Netherlands | nl | 2 | 4 | 1 | 3 | 3 | 3 | B4, Dota |
| Norway | no | 2 | 3 | 1 | 3 | 2 | 3 | B4, CS, Dota, Destiny |
| Peru | pe | 3 | 1 | 2 | 4 | 2 | 2 | CS, Dota |
| Philippines | ph | 4 | 2 | 3 | 2 | 2 | 2 | CS, Dota |
| Poland | pl | 3 | 3 | 3 | 4 | 2 | 2 | B4, CS, Dota, Destiny |
| Portugal | pt | 3 | 2 | 2 | 4 | 2 | 2 | B4 |
| Romania | ro | 4 | 2 | 2 | 4 | 3 | 1 | CS, Dota |
| Russia | ru | 4 | 2 | 2 | 4 | 4 | 1 | B, CS, Dota, Destiny |
| Serbia | rs | 4 | 2 | 2 | 4 | 3 | 2 | Dota |
| Singapore | sg | 3 | 1 | 2 | 1 | 3 | 2 | Dota |
| South Africa | za | 2 | 3 | 3 | 2 | 1 | 3 | B4, CS |
| South Korea | kr | 3 | 1 | 2 | 4 | 4 | 2 | B4 |
| Spain | es | 3 | 3 | 2 | 4 | 2 | 2 | B4 |
| Sweden | se | 2 | 3 | 1 | 2 | 3 | 4 | B4, CS, Dota, Destiny |
| Switzerland | ch | 2 | 3 | 3 | 3 | 3 | 3 | B4 |
| Thailand | th | 3 | 1 | 2 | 3 | 2 | 2 | Dota |
| Turkey | tr | 3 | 2 | 2 | 4 | 2 | 2 | B4, CS, Dota, Destiny |
| Ukraine | ua | 4 | 2 | 2 | 4 | 3 | 1 | B4, CS, Dota |
| United Kingdom | gb | 2 | 4 | 3 | 2 | 3 | 3 | B4, CS, Dota, Destiny |
| United States | us | 2 | 4 | 3 | 2 | 2 | 3 | B4, CS, Dota, Destiny |
| Vietnam | vn | 3 | 1 | 2 | 2 | 3 | 2 | Dota |

but merely serve as a pragmatic basis for research. The table also includes for each country for which games we have data.

## VII. Results

We used a one-way Analysis of Variance (ANOVA) to determine whether cross-cultural differences exist in playing styles. We performed ANOVA tests to determine for playing style variables the proportion variance explained by nationalities (VII-A) and by Hofstede dimensions (VII-B). Note that each individual player gets assigned to the Hofstede group to which their country is assigned. To determine the relation between national culture and playing style, we used t-SNE (VII-C). We used classification to predict nationality and the categories of cultural dimensions based on playing style (VII-D).

### A. Nationality and Playing Style

We analyzed the effect of nationality on the playing styles in our datasets. Top features with the highest proportion variance explained ($\eta^2$) are shown in Tables II to V in descending order of variance explained.

*a) Battlefield 4:* In Table II it is shown from the 15 features with most variance explained that in *Battlefield 4* nationality affects play-time (rounds played), achievements (medals, ribbons per round, and assignments), and social behavior (suppression assists, team score, kill assists, and savior kills). Experience related features such as 'rounds played,' 'medals,' and 'ribbons per round' are at the top of these features. This can be interpreted as nationality influencing the players' engagement and skills [19].

TABLE II: ANOVA test on the effect of nationality on 15 features with the highest proportion variance explained in *Battlefield 4* with p=.001 and df=(28, 14877).

| feature | F | $\eta^2$ |
|---|---|---|
| Rounds played | 124.74 | .190 |
| Medals | 59.40 | .101 |
| Ribbons per round | 55.32 | .094 |
| Light Machine Gun shots fired | 4.15 | .070 |
| Rounds finished/Rounds played | 37.31 | .066 |
| Assault Rifle shots fired | 37.26 | .066 |
| Suppression assists | 35.37 | .062 |
| Gadget accuracy | 32.37 | .057 |
| Assignments | 28.26 | .051 |
| Sniper Rifle shots fired | 28.21 | .050 |
| Team score | 27.30 | .049 |
| Kill assists | 24.06 | .043 |
| Vehicle damage | 23.86 | .043 |
| Shotgun shots fired | 23.68 | .043 |
| Savior kills | 23.37 | .042 |

TABLE III: ANOVA on the effect of nationality on the 15 features with highest proportion variance explained in *Counter-Strike* with p=.001 and df=(25, 13936).

| feature | F | $\eta^2$ |
|---|---|---|
| Total Rounds Map Nuke | 58.597 | .095 |
| Team Tactics Achievements Ratio | 49.015 | .081 |
| Total Wins Map Nuke | 48.790 | .080 |
| Combat Skills Achievements Ratio | 47.762 | .078 |
| Global Experience Achievements Ratio | 39.383 | .066 |
| Weapon Specialist Achievements Ratio | 39.283 | .066 |
| Total Rounds Map Dust2 | 37.398 | .063 |
| Total Wins Map Dust2 | 34.986 | .059 |
| Arms Demolition Achievements Ratio | 34.766 | .059 |
| Total Rounds Map Inferno | 31.538 | .053 |
| Total Wins Map Inferno | 3.819 | .052 |
| Total Wins Pistolround | 28.591 | .049 |
| Total Rounds Map Train | 26.449 | .045 |
| Total Kills Enemy Weapon | 26.061 | .045 |
| Total Rounds Played | 23.639 | .041 |

*b) Counter-Strike:* Table III shows the 15 features with highest proportion variance explained in *Counter-Strike*. The results show that countries may have preferences for particular battle maps. Furthermore, a considerable amount of variance is explained by nationality in all five 'achievement ratio' features. This means that players from particular countries are more achievement-oriented than players from other countries.

*c) Dota 2:* Table IV shows the effect of nationality on the 15 features with highest proportion variance explained in *Dota 2*. The 'total matches' feature is at the top, meaning that players from certain countries play more matches than players from other countries. The second feature is 'ping.' By using a ping, a player alerts team members about an event at a specific location. The high proportion variance of 'ping' and 'total words said' shows that players from different countries may have different styles of communication. Furthermore, a considerable amount of variance is explained by several 'hero' features. A player's choice for a hero depends on their

TABLE IV: ANOVA on the effect of nationality on the 15 features with highest proportion variance explained in *Dota 2* with p=.001 and df=(29, 15330).

| feature | F | $\eta^2$ |
|---|---|---|
| Total Matches | 64.527 | .109 |
| Ping | 55.628 | .095 |
| Total Words Said | 5.871 | .088 |
| Hero Damage | 29.065 | .052 |
| Deaths | 25.370 | .046 |
| Level | 21.299 | .039 |
| XP per Min Avg per Match | 2.513 | .037 |
| Hero Ranged | 18.644 | .034 |
| Assists | 18.369 | .034 |
| Purchase Force Staff | 17.453 | .032 |
| Hero Disabler | 17.129 | .031 |
| Purchase Blink | 16.950 | .031 |
| Tower Damage | 16.864 | .031 |
| Hero Support | 16.799 | .031 |
| Hero Jungler | 16.401 | .030 |

TABLE V: ANOVA test on the effect of nationality on 15 features with the highest proportion variance explained in *Destiny* with p=.001 and df=(40, 10440).

| feature | F | $\eta^2$ |
|---|---|---|
| Kill Distance | 209.6 | .445 |
| Player DTR score | 191.4 | .423 |
| Life Span | 186.5 | .416 |
| Assists Per Game | 168.5 | .392 |
| Precision Kills | 145.5 | .358 |
| Assists | 133.3 | .338 |
| Ability Kills | 131.3 | .334 |
| Player kills | 128.8 | .330 |
| Orbs Dropped | 91.2 | .330 |
| Deaths | 119.8 | .314 |
| Player Games | 119.5 | .314 |
| Player time Played | 112.7 | .301 |
| Revives Performed | 104.0 | .284 |
| Revives Received | 98.9 | .274 |
| Orbs Gathered | 94.11 | .265 |

preferred in-game role. This may therefore indicate differences in in-game roles between different countries.

*d) Destiny:* Table V shows the top-15 features with the highest proportion variance explained in *Destiny*. 'Kill distance' is the top feature; it is influenced by the players' shooting behavior and types of weapons used. The second feature is 'DTR score,' which is a combined rating, calculated by the Destiny Tracker site, for all skill-based features of playing style, such as kills, medals, assists and deaths. This entails that there is a considerable difference in playing skills between certain countries. Several features related to 'kills' also explain a high amount of variance, as do features that relate to cooperative behavior such as 'assists' and 'revives.'

### *B. Hofstede Dimensions and Playing Style*

In a separate series of ANOVA tests, we analyzed the effect of Hofstede dimensions on the playing styles in our datasets (Tables VI to IX). We left out the playing style features for which we found the interpretation is ambiguous.

*a) Battlefield 4:* Table VI shows that for *Battlefield 4* in particular Individualism (IDV) explains most variance in

TABLE VI: Proportion variance explained by each Hofstede dimension category in *Battlefield 4* with df=(3, 14902).

| feature | PD | IDV | MA | UA | LTO | IDL |
|---|---|---|---|---|---|---|
| Medals | .011 | .037 | .009 | .002 | .023 | **.040** |
| Ribbons per round | .010 | .035 | .009 | .003 | .023 | **.037** |
| Assignments | .006 | **.015** | .003 | .003 | .010 | **.015** |
| LM Gun shots fired | .014 | **.058** | .004 | .003 | .023 | .021 |
| AR shots fired | .020 | **.050** | .013 | .010 | .016 | .028 |
| SR shots fired | .011 | **.034** | .012 | .004 | .016 | .020 |
| Shotgun shots fired | .011 | **.028** | .010 | .005 | .010 | .021 |
| Suppression assists | .008 | **.037** | .005 | .000 | .024 | .020 |
| Team score | .004 | **.028** | .004 | .000 | .014 | .012 |
| Kill assists | .008 | **.027** | .008 | .003 | .013 | .015 |
| Savior kills | .008 | **.030** | .006 | .003 | .012 | .014 |
| Sum of variance | .111 | **.379** | .083 | .036 | .184 | .243 |

the playing style features, namely for 9 of the 11 features. For the resulting two features, 'medals' and 'ribbons per round,' Individualism explains almost as much variance as Indulgence, the dimension which explains most variance for those two features. The explanatory power of Individualism is not surprising, as *Battlefield 4* is a multi-player game in which players co-operate in teams and are rewarded for team-play, but can choose to play alone [19].

The first three features, 'medals,' 'ribbons per round,' and 'assignments,' reflect award-collecting behavior, and are most explained by Indulgence (IDL). Award-collecting behavior is related to restrained societies, because awards are clear status symbols that represent a player's performance in the game.

The variance of 'light machine gun shots fired,' 'assault rifle shots fired,' 'sniper rifle shots fired,' and 'shotgun shots fired', is most explained by the Individualism (IDV) dimension, for which we see no obvious explanation.

The variance of the last four features, 'suppression assists,' 'team score,' 'kill assists,' and 'savior kills,' is again most explained by the Individualism (IDV) dimension. These four features express social and cooperative behavior. This result is not unexpected, as collectivist countries tend to consider in-group goals as more important than personal goals.

*b) Counter-Strike:* Table VII shows that for *Counter-Strike* the Individualism dimension explains most variance in 14 of the 15 features. All 'map' features are most explained by Individualism, which seems to indicate that the gameplay features of particular maps are appreciated more by individualistic countries than collectivistic countries, and vice versa. It may also indicate a preference for strategic gameplay of certain cultures, as the Nuke map (ranking high among the features) is strategically among the most balanced maps. The 'achievement' features are all most explained by Individualism. The mean value of all these features increases as the value for Individualism increases, meaning that players from individualistic countries collect more achievements and thus show more achievement-oriented behavior than players from collectivistic countries.

All remaining features are, again, most explained by Individualism, except 'total weapons donated.' The Masculinity dimension explains the highest proportion variance in this

TABLE VII: Proportion variance explained by each Hofstede category in *Counter-Strike* where df=(3, 13958). (TTA: Team Tactics Achievements, CSA:Combat Skills Achievements, TK:Total Kills, TR:Total Rounds, TW:Total Wins)

| feature | PD | IDV | MA | UA | LTO | IDL |
|---|---|---|---|---|---|---|
| TR Map Nuke | .038 | **.061** | .015 | .025 | .002 | .014 |
| TTA Ratio | .020 | **.043** | .017 | .018 | .003 | .006 |
| TW Map Nuke | .031 | **.050** | .013 | .019 | .002 | .012 |
| CSA Ratio | .023 | **.043** | .016 | .018 | .001 | .006 |
| TR Map Dust2 | .013 | **.025** | .006 | .008 | .001 | .011 |
| TW Map Dust2 | .012 | **.023** | .006 | .007 | .001 | .010 |
| TR Map Inferno | .009 | **.031** | .012 | .015 | .006 | .008 |
| TW Map Inferno | .009 | **.030** | .012 | .015 | .006 | .008 |
| TW Pistolround | .004 | **.015** | .011 | .008 | .006 | .005 |
| TR Map Train | .013 | **.025** | .006 | .011 | .001 | .011 |
| TK Enemy Weapon | .002 | **.013** | .012 | .008 | .003 | .006 |
| Weapons Donated | .001 | .009 | **.015** | .003 | .004 | .009 |
| TK Enemy Blinded | .001 | **.012** | .009 | .006 | .002 | .006 |
| TK Zoomed Sniper | .011 | **.020** | .005 | .006 | $<$.001 | .005 |
| TW Map Train | .008 | **.016** | .003 | .006 | $<$.001 | .006 |
| Sum of variance | .275 | **.518** | .199 | .230 | .050 | .135 |

feature. The mean value of 'total weapons donated' increases as the value for Masculinity decreases. This is not surprising, as a low value for Masculinity represents a society with preference for cooperation and caring for others.

*c) Dota 2:* Table VIII shows that also for *Dota 2*, the Individualism dimension explains most of the proportion variance in playing styles. The mean value of 'total matches' increases as the value for Individualism increases. There are several possible explanations for this finding. One is that players from individualistic countries are more likely to leave a match before the match is over; another is that players from individualistic countries simply play a higher variety of games. The cooperative behavior features such as 'ping' and 'assists' are most explained by Individualism. This is not unexpected, as collectivistic countries emphasize cooperative behavior. The feature 'hero jungler' is a lone-ranger role, and unsurprisingly associated with Individualism. The features 'hero disabler' and 'hero support' resemble supportive in-game roles. These features are most explained by Individualism and Uncertainty Avoidance, for which we see no obvious explanation.

*d) Destiny:* Table IX summarizes the proportion variance explained by Hofstede dimensions in *Destiny*. Similar to the other video games in our study, the Individualism dimension explains the most of proportion variance, but the Masculinity dimension and Power Distance dimension also explain a considerable proportion variance. The 'kills' features such as 'kill distance,' 'DTR score,' and 'precision kills' are all explained by Individualism. These features relate to particular tactics used by players, and indicate that players from individualistic countries may prefer different tactics than players from collectivistic countries.

The two 'revives' features are most explained by the Masculinity dimension. A possible explanation is that in revives are a sign of cooperation, which is more common for national cultures which are more feminine.

TABLE VIII: Proportion variance explained by each Hofstede dimension category in *Dota 2* with df=(3, 15356).

| feature | PD | IDV | MA | UA | LTO | IDL |
|---|---|---|---|---|---|---|
| Total Matches | .017 | .032 | .009 | **.021** | .004 | .009 |
| Ping | .008 | **.028** | .004 | .012 | .014 | .021 |
| Total Words Said | .001 | .009 | .004 | .006 | **.027** | .034 |
| Hero Damage | .009 | **.015** | .004 | .009 | .002 | .006 |
| Deaths | .008 | .013 | .007 | **.018** | .003 | .013 |
| Level | .006 | **.007** | .004 | .006 | .002 | .005 |
| XP per Min Avg | .008 | **.009** | .003 | .006 | .001 | .005 |
| Hero Ranged | .007 | **.018** | .003 | .004 | .001 | .004 |
| Assists | .006 | **.014** | .006 | $<$.001 | .005 | .009 |
| Purch. Force Staff | $<$.001 | .007 | .001 | **.015** | $<$.001 | .004 |
| Hero Disabler | .004 | **.011** | .002 | .010 | $<$.001 | .002 |
| Purchase Blink | $<$.001 | .004 | .002 | **.008** | .001 | .006 |
| Tower Damage | .001 | **.006** | .003 | .005 | .001 | .003 |
| Hero Support | .008 | **.015** | .005 | .007 | .001 | .004 |
| Hero Jungler | .011 | **.013** | .002 | **.013** | .001 | .003 |
| Sum of variance | .122 | **.253** | .080 | .165 | .075 | .147 |

TABLE IX: Proportion variance explained by each Hofstede dimension category in *Destiny* with df=(3,10477).

| feature | PD | IDV | MA | UA | LTO | IDL |
|---|---|---|---|---|---|---|
| Kill Distance | .040 | **.080** | .048 | .026 | .045 | .072 |
| Player DTR score | .074 | **.081** | .059 | .038 | .008 | .011 |
| Life Span | .039 | **.093** | .064 | .023 | .047 | .064 |
| Assists Per Game | .023 | .032 | .026 | .028 | .029 | **.046** |
| Precision Kills | .053 | **.104** | .062 | .028 | .018 | .028 |
| Assists | .048 | **.103** | .060 | .023 | .019 | .023 |
| Ability Kills | .045 | **.102** | .065 | .024 | .021 | .022 |
| Player kills | .056 | **.070** | .045 | .038 | .006 | .008 |
| Orbs Dropped | .048 | **.104** | .056 | .025 | .019 | .027 |
| Deaths | .038 | **.097** | .065 | .018 | .024 | .016 |
| Player Games | **.052** | .050 | .046 | .037 | .005 | .004 |
| Player Time Played | **.051** | .047 | .042 | .034 | .005 | .004 |
| Revives Performed | .037 | .057 | **.063** | .023 | .018 | .011 |
| Revives Received | .035 | .055 | **.061** | .023 | .018 | .009 |
| Orbs Gathered | .036 | **.090** | .045 | .025 | .016 | .020 |
| Sum of variance | .673 | **1.167** | .805 | .413 | .297 | .363 |

### C. National Culture and Playing Style

To investigate the relation between playing style and nationality we employed t-SNE. t-SNE visualizes high dimensional data in two dimensions that represent structures at different scales [26]. Linderman and Steinerberger [27] proved that t-SNE has the capability to find relevant clusters. t-SNE has been applied to different domains including player modeling. For instance, Alves et al. [28] used t-SNE to distinguish paying players from non-paying players. Ryan et al. [29] used t-SNE to find to what extent video game descriptions reflect the similarity between video games.

We calculated the average over all playing style variables for all the players of a country. We projected the resulting vectors into 2-dimensional space, using the t-SNE algorithm. Figure 1 compares playing styles and nationality in different games. The subfigures indicate differences and similarities in playing styles between countries by the distance between the countries, i.e., countries which show similar playing styles are closer together.

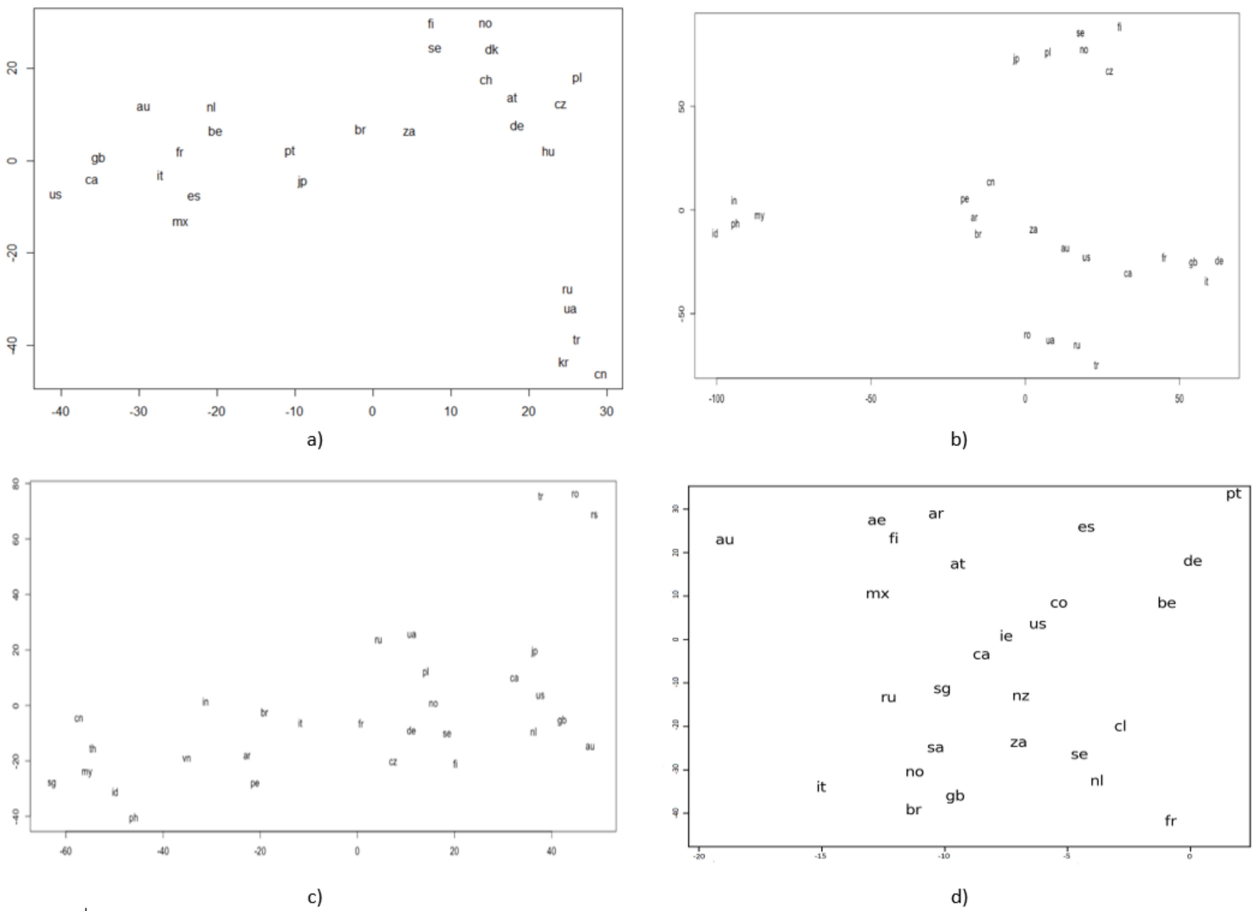


Fig. 1: Comparing playing styles and nationality in different games. a) *Battlefield 4*. b) *Counter-Strike*. c) *Dota 2*. d) *Destiny*.

*a) Battlefield 4:* Figure 1-a shows the comparison between playing styles of countries in *Battlefield 4*. Note that Russia, Ukraine, Turkey, South Korea, and China are in the lower right corner of the image and are dissociated from the other countries. China and South Korea are the only countries in this analysis in the ‘low’ group on Individualism, and the other three countries are in the ‘medium low’ group on Individualism. Moreover, Russia, Ukraine, and China are the only countries in the ‘low’ group on Indulgence, and the other countries are in the ‘medium low’ group. Thus, we consider it unsurprising that these countries differentiate from the other countries on average playing style.

Note also that the Scandinavian countries (Denmark, Finland, Norway and Sweden) are close together at the top of the graph. Moreover, we observe that the Anglo-Saxon countries (US, Canada, Great Britain, and Australia), which are culturally very similar, are clustered at the left of the graph. Next to them, we find a cluster of typical Western European countries: Netherlands, Belgium, France, Italy, and Spain, with Mexico very close to Spain [19].

*b) Counter-Strike:* As Figure 1-b shows, Romania, Ukraine, Russia, and Turkey are grouped at the bottom of the figure. These countries are all score ‘high’ on Uncertainty Avoidance, and ‘medium low’ on Masculinity.

Furthermore, at the left of the figure four Asian countries (India, Malaysia, Philippines, and Indonesia) are separated from the other countries. These countries have comparable scores for each of the Hofstede dimensions.

Several other groups of countries can be recognized as clusters. The South American countries (Peru, Argentina, and Brazil) are close together in the middle (with China being very close to them). As with the *Battlefield 4* figure, the Anglo-Saxon countries are again close to each other, as are the Scandinavian countries.

*c) Dota 2:* Figure 1-c shows the results of the t-SNE visualization of the country vectors for *Dota 2*. Although the differences between the countries are less clear, one can still recognize clusters of countries with comparable national cultures. Most Asian countries are grouped at the lower left and the Anglo-Saxon countries are clustered at the right. Moreover, Serbia, Romania, and Turkey are separated from the other countries at the top right of the figure. All these countries have comparable scores for most of the Hofstede dimensions.

*d) Destiny:* The comparison between playing styles of countries in *Destiny* is shown in Figure 1-d. For *Destiny* clusters are not clear. A potential explanation is that *Destiny*, which has only three different player classes, offers fewer possibilities to express cultural differences. Another potential explanation is that the game appeals to a more constricted type of player, and thus there can be found less variability in playing styles. The fact that Asian countries are hardly represented in our *Destiny* dataset is a sign of that.

*e) Comparing countries:* To demonstrate how different playing styles for players in particular countries can be, in Figure 2 we have clustered for each dataset all the players from the US versus all the players from China (except for *Destiny*, where we have no players from China, and thus we picked players from Brazil, which is far away from the US in Figure 1-d).

Figure 2-a shows a t-SNE on playing style for Chinese and US players in *Battlefield 4*. The figure shows that, in general, there is a clear difference in playing style of players from these countries. According to the Hofstede dimensions, China and the US are indeed quite different, in particular where Individualism, Indulgence, and Long-Term Orientation are concerned.

Figure 2-b shows Chinese players vs. US players in *Counter-Strike*. Most Chinese players are clustered at the left side of the figure, while most US players are at the right. We examined many other pairs of countries for *Counter-Strike*, and many show similar differences; some of these even more clear than the China/US plot.

Figure 2-c indicates some differences in playing style between Chinese and US players in *Dota 2*. US players are centered in the middle, while Chinese players are overall more spread out. Other pairs of countries show even clearer differences for *Dota 2* than the China/US plot.

For *Destiny*, we compared US players with Brazilian players. In Figure 2-d we can see that there is relatively little overlap between the players from US and the players from Brazil, a picture similar to what we could see for the US and China for *Battlefield 4*. What is notable about this figure is that there seem to be many little clusters of players with playing styles that are very closely related. This may be the result of the different game modes of *Destiny*, combined with the limited selection of character classes.

What is striking in all these figures, is the fact that the US players tend to overlap a lot with the players they are compared to, but that the other country (China or Brazil) has more 'unique' players. A possible explanation is that the US is more a 'melting pot' of players where playing styles which are typical for other countries are also represented.

### *D. Predicting Nationality and Cultural Dimensions*

We formulated the prediction of Hofstede cultural dimensions as a multi-class classification. For each cultural dimension a classification model was developed. Playing style features represented the input of the model. The output was the score value for cultural dimension, varying between 1 and 4. As classifiers we used Linear Regression, Random Forest, Support-Vector Machines (SVM), and Neural Networks. We applied these classifiers for all cultural dimensions in all four video games. We split each dataset into a training set consisting of 70% of the data, and a test set with the remainder of the data.

Classification accuracy, i.e., the percentage of correctly classified samples, was used to evaluate the different models. Five-fold cross-validation was performed on the training set to estimate the performance of the models using a particular set of parameters, and the stratified option ensured that the training samples were equally distributed. For each model, the parameter set which had the best cross-validation score on the training set was selected. Finally, the accuracy scores on the test set were compared to the accuracy of the ZeroR baseline model to see if the model was able to determine the appropriate Hofstede dimension on the basis of the input parameters. The results are shown in Tables X to XIII. The values in bold indicate models with higher accuracy.

The results show that nationality can be predicted considerably better than the baseline. Usually this is because some countries can be predicted quite well – we found that in particular Asian countries can be distinguished from Western countries. The performance of nationality prediction in *Destiny* is lower than the other games in the study. This also might be due to including fewer Asian countries in the *Destiny* dataset.

The prediction of cultural dimensions also improves upon

TABLE X: Predicting nationality and cultural dimension from playing styles in *Battlefield 4*

| target | baseline | RF | LR | SVM | NN |
|---|---|---|---|---|---|
| Nationality | 3.48 | 15.49 | **18.00** | 17.45 | 16.79 |
| PD | 41.33 | 47.35 | 48.11 | **48.62** | 47.30 |
| IDV | 41.29 | 46.94 | 49.97 | **5.34** | 47.66 |
| MA | 44.87 | 47.32 | **47.63** | 47.56 | 46.42 |
| UA | 48.25 | 5.24 | 51.31 | **51.93** | 31.07 |
| LTO | 34.51 | 42.43 | 44.25 | **44.46** | 38.89 |
| IDL | 44.94 | 49.83 | 52.00 | **52.72** | 52.09 |

TABLE XI: Predicting nationality and cultural dimension from playing styles in *Counter-Strike*

| target | baseline | RF | LR | SVM | NN |
|---|---|---|---|---|---|
| Nationality | 3.87 | 16.79 | 18.08 | **19.51** | 16.65 |
| PD | 38.45 | 49.77 | 49.80 | **5.13** | 48.98 |
| IDV | 38.49 | 48.30 | 47.58 | **48.48** | 48.37 |
| MA | 53.81 | **55.71** | 53.71 | 54.57 | 55.25 |
| UA | 42.28 | **54.57** | 53.42 | 53.85 | 54.53 |
| LTO | 42.36 | 44.36 | **44.65** | 44.11 | 43.61 |
| IDL | 42.32 | **48.55** | 46.72 | 48.37 | 47.19 |

TABLE XII: Predicting nationality and cultural dimension from playing styles in *Dota 2*

| target | baseline | RF | LR | SVM | NN |
|---|---|---|---|---|---|
| Nationality | 3.35 | 15.63 | 17.48 | **18.13** | 16.70 |
| PD | 36.69 | **48.27** | 45.61 | 47.49 | 47.66 |
| IDV | 36.56 | 44.60 | 44.47 | **45.21** | 45.05 |
| MA | 43.29 | **52.05** | 48.86 | 49.15 | 49.54 |
| UA | 39.94 | 5.85 | 5.55 | 51.17 | **51.33** |
| LTO | 43.29 | **47.40** | 45.50 | 46.74 | 46.35 |
| IDL | 49.97 | **55.66** | 54.39 | 53.84 | 54.23 |

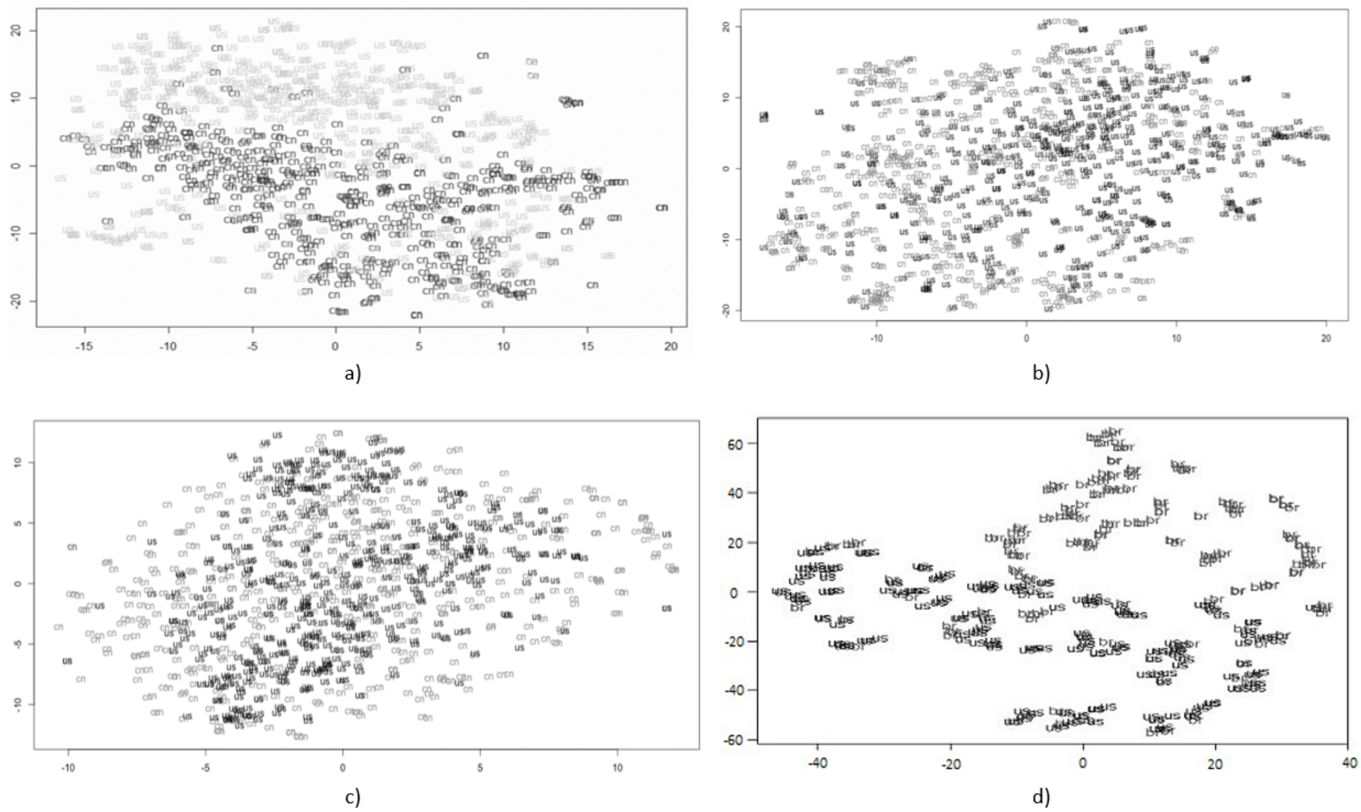

Fig. 2: Comparing playing styles in different video games. a) China vs. US in *Battlefield 4*. b) China vs. US in *Counter-Strike*. c) China vs. US in *Dota 2*. d) Brazil vs. US in *Destiny*.

TABLE XIII: Predicting nationality and cultural dimension from playing styles in *Destiny*

| target | baseline | RF | LR | SVM | NN |
|---|---|---|---|---|---|
| Nationality | 3.70 | 2.37 | **7.70** | 6.65 | 4.63 |
| PD | 31.43 | 22.85 | **34.44** | 31.54 | 33.60 |
| IDV | 25.81 | 13.03 | 24.38 | 17.67 | **28.26** |
| MA | 35.90 | 48.92 | **61.64** | 61.02 | 54.60 |
| UA | 3.56 | **5.24** | 32.66 | 37.33 | 44.22 |
| LTO | 31.43 | 36.6 | 19.71 | 28.6 | **39.43** |
| IDL | 38.10 | 3.00 | 46.09 | 38.76 | **51.42** |

the baseline for almost every dataset (also in Tables X to XIII). The performance of the prediction depends on the chosen video game. In *Battlefield 4*, IDV, LTO, and IDL are predicted more accurately than the other cultural dimensions. For *Counter-Strike*, this holds for PD, IDV, and UA. For *Dota 2*, PD, IDV, and UA are predicted better than the other cultural dimensions. In *Destiny*, MA and IDL are predicted better than the other cultural dimensions. We observe that Individualism (IDV) is predicted with considerable accuracy in all studied video games, except *Destiny*; a possible explanation is that we had less access to players from Asian countries in our *Destiny* dataset. These observations are in line with what we found in section VII-B, where we saw that Individualism explains the highest proportional variance in most cases.

## VIII. Discussion

We analyzed four popular Massively Multiplayer Online Games (MMOGs) across Western and non-Western countries and we looked at the relation between nationality, national culture, and playing style. Our research demonstrated clear differences in the playing styles of players from different countries. Moreover, we found that in many cases, the playing styles of people in countries which can be considered similar in culture (Anglo-Saxon, Scandinavian, Asian, Western-European) have clear similarities, as the average playing styles of their citizens seem to form clusters when using t-SNE dimensionality reduction. This demonstrates that cultural differences in playing styles can be recognized.

In part of our analysis we did not consider countries as separate entities, but characterized them according to the Hofstede dimensions. Such a characterization can be called a “national culture.” We found clear indications that national culture has an influence on playing styles, and thus on gameplay preferences. This entails that game development companies which aim to have their games played world-wide, need to take into account the fact that different countries may have different preferences for gameplay elements. The least that game designers could do would be to run early test sessions with a game in countries with widely different cultures, to see whether relatively simple enhancements to a game could make the game more supportive of playing styles that are prevalent in particular countries.

Naturally, while differences between countries as a whole can be recognized, different players will have wildly different styles, so when comparing players from two countries, their styles are likely to overlap. We observed this in the t-SNE visualizations for individual players from different countries. However, we could still observe that the overlap is only for part of the player base, while large groups of players could be labeled as "typical for their country."

## IX. Conclusion

We studied playing styles in four popular MMOGs across different countries. We analyzed the relation between nationality, cultural dimensions, and playing styles. Our findings show that not only nationality and cultural dimensions have relationship with playing styles, but also that players from countries with similar national cultures seem to have similar playing styles. It should be noted, however, that we cannot conclude that there exists a direct causal relationship between culture and playing style. Third-variable explanations for the relationships might play a role, for instance, explanations related to the economy of the countries. However, considering that a relationship between culture and playing style exists, it may be prudent to take national cultures into account when designing games that should have an international appeal. In particular, the Hofstede dimension "Individualism" explained most of the variance in playing styles between national cultures for the games that we examined.

In conclusion, we have demonstrated that a player's culture is related to their playing style, and that insights into culture can be gained from examining playing style. In this research we were restricted by our limited access to player information, which we mostly got from public websites. Thus, in our examination of player culture we were restricted to nationality. However, cultural values are expressed by more player features, such as their religion, their birth place, and their family values. Game publishers often have access to information of this kind for individual players. Expanding the current research using such information could increase its impact considerably.

## Acknowledgements

The authors acknowledge the work on this topic by De Vries. The work on *Battlefield 4* was originally done in collaboration with her, and reported on in her thesis [19]. We summarized some of that work in this article as it helps drawing the final conclusions. Note: The datasets used in this article will be made available online.

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