Personality Matters: Incorporating Detailed User Attributes and Preferences into the Matchmaking Process

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Abstract

Finding ways of reducing undesired behavior in online interactions is at the forefront of the social computing research agenda. One promising way to reduce perceived "bad behavior" is by matching members of online social environments with corresponding behavioral preferences. We present an empirical study (N = 267) of an experimental system for matching users. As a test bed we chose the online game MechAssault, which largely supports one-off encounters within a socially homogenous population. Even within this population we found great variability in the way users selected their gaming partners. One type of player chose partners mainly on their skill, another mainly on a friendly gaming personality, and a third preferred aggressive players. Detailed analyses revealed the underlying attributes of user profiles that generated these user types. The findings suggest that a matchmaking system can better promote desired online interactions than the enforcement of uniform behavioral standards.

1. Introduction

Online gaming is gaining in relevance, both in terms of the growth in user volume [9] and also in the mass adoption of novel technologies. The latest generation of online gaming consoles, such as the Xbox 360, comes with sophisticated tools to find and communicate with other users. Many see these consoles as the hub of the future digital home [9]. As such, these console systems provide an interesting testing ground for established concepts and theories from the fields of computer-supported collaborative work (CSCW) and computer-supported communications (CMC). One of the predictions from research in these fields is that richer communication channels can lead to higher rates of cooperation and norm-compliant behavior [13], [1]. However, many users of voice-enabled online gaming platforms report verbal aggression from other gamers [5]. Rather than preventing them, the voice channel appears to make these confrontations more harmful. In addition to rich media channels, approaches to support norm-compliant behavior, such as reputation systems, have been implemented in current online gaming systems; but the problem of unpleasant online encounters persists [11].

These undesirable interactions may continue in part because current online gaming matchmaking systems are largely based on impersonal attributes such as users' connection speed, number of players in a game, and occasionally skill level. This lack of individuating information is often cited as one of the attractions of online interactions, as it liberates users from stereotyping [8]. However, it also stands in stark contrast to how people navigate social spaces offline. Groups or clubs are joined based on location and access rules that increase the likelihood of meeting like-minded others and, importantly, on personal characteristics like appearance and friendliness.

Based on these observations we pose a new question. Can we utilize matchmaking to reduce perceived norm-violating behavior online? To this end we investigate how the often subtle, but important interpersonal attributes people utilize in physical world social interactions can be used for an online gamer matchmaking system. In this paper we first introduce the conceptual background to our approach. The main section of the paper describes a multi-stage study in which we identified relevant gamer attributes, created an online experiment that allowed players to create profiles and–at a later date–to choose gaming partners. We describe how we analyzed gaming partner preferences and self-described behavioral attributes to infer whether matchmaking could reduce perceived "bad" behavior. We conclude with recommendations for the design of matchmaking systems in online gaming and other contexts.

2. Background

2.1 One-Off vs. Repeated Encounters

One factor that may help in explaining the occurrence of perceived inappropriate behavior is the continuity of interactions: whether interactions are one-off with a low likelihood of future encounters between two players, or whether they form part of an evolving relationship with the possibility for repeat encounters. It is well-established that the expectation of future interactions, the “shadow of the future” [1], has a strong positive effect on norm-compliance. Much research in CMC and CSCW focused on continuing interactions, as these are typical for a workplace or classroom context, for example. With the proliferation of social online platforms, however, casual one-off interactions with others about whom little is known and with whom one is unlikely to interact in the future are becoming increasingly common. To be sure, such interactions have long existed in a professional setting (e.g. in call-centre interactions). But in those circumstances norm-compliant behavior is ensured by institutional embedding, e.g. via corporate policies and selection processes. Systems that specialize in one-off encounters without institutional embedding are a relatively novel phenomenon. Gaming platforms that offer an instant match with another player are probably the most prevalent example, but these encounters do also exist in other contexts, such as online support groups, online dating, or resource sharing systems.

2.2 Current Approaches to Norm-Compliance

Cooperation, trust, and norm-compliance have a long research tradition in the fields of CMC and CSCW. Observations of teams working together over distance suggested that “trust breaks down” [17] over distance. Many of the approaches towards encouraging cooperative and pro-social behavior that were subsequently researched in CMC and CSCW made their way into today’s online gaming platforms: policing [16], rich modalities [1], [5], [13], stable identities [1], and reputation systems [7], [12] can be found in gaming environments. However, as the continuing concern about harmful behavior on these platforms indicates, these approaches are subject to limitations:

Policing an online gaming environment is costly, does not scale well, and – most importantly – it is reactive.

Richer communication channels do not only support norm-compliant behavior during game-play, but can also increase the immediacy of aggressive behavior that may be afforded by the setting of the game.

Stable identities and **block lists** can be a deterrent to inappropriate behavior if there is only a limited pool of gaming partners and potential wrongdoers thus have to expect their victims to block them in future encounters. However, in large online gaming communities that mainly cater to short one-off interactions, this may not be a sufficient incentive for adequate behavior.

Reputation systems overcome this shortcoming of block lists but they require individuals to enter and share truthful feedback on individual gaming encounters.

More importantly, all these approaches assume previously agreed and shared definitions of what constitutes “good” and “bad” behavior (i.e. shared behavioral norms) within the user population for a particular game. In this paper we discuss why this may not be a valid assumption and how differences in behavioral attributes and preferences, if they are found to exist in a population, could be used to improve perceived behavior.

2.3 Differing Norms in Sub-Cultures

It is well-established that several sub-cultures or tribes exist within societies or cultures. In some instances behavioral norms within these tribes deviate from mainstream cultures to such an extent that behavior that constitutes norm-violation in the mainstream culture is required as signal of membership in the sub-culture – think of hairstyle in the case of punks or silence among monks.

Similar observations have been made for the societies that are formed by the players of multi-user dungeons (MUD) and massive multiplayer online games (MMORPG). In these environments gamers interact repeatedly over extended periods of time and form communities or clans with distinct cultures [2]. Several player typologies have been defined for these gaming environments. Bartle [2], for instance, categorized MUD players into Killers, Achievers, Socialisers, and Explorers. Killers enact an aggressive gaming personality that suits the context of the game, but may break the expectations of Socialisers who apply the conventions of real-word encounters. For a

Socialiser an encounter with a Killer is likely to be experienced as distressing and unpleasant.

While differing behavioral norms in real-world interactions and MUDs or MMORPGs have been widely investigated, there has been little research into their existence in the one-off gaming encounters that are now so typical for many gaming platforms. In many of these, players are paired just for one gaming session based on impersonal attributes. If distinct norms in the player populations of such games exist, matchmaking based on these impersonal factors alone is likely to result in encounters with perceived "bad" behavior that was not intended to be norm-violating.

There is anecdotal evidence that distinct behavioral norms do also exist for one-off games [11]. For example, many players of voice-enabled Xbox Live games use the voice channel to enact an aggressive gaming alter ego to fit the setting of the game. While the resulting 'trash-talking' is enjoyed by many players as part of the gaming experience it can be seen as hostile by others [11]. Thus, a bad gaming experience in these environments may not necessarily be the result of intentional misbehavior but can stem from different expectations of what creates a good game. If this is the case, then intelligent matchmaking may be another route to improving perceived norm-compliance within a gaming population.

2.4 Supply and Demand of Attributes

A second condition must be met for matchmaking to be a successful approach towards reducing perceived misbehavior. The sub-populations with distinct behavioral norms must complement each other with regard to their exhibited and preferred behavioral attributes. In other words, matchmaking can only be successful as an approach to improving perceived behavior if there is matching supply and demand for specific behaviors within a gamer population. This condition would be most easily met if gamers differed in relevant behavioral attributes and preferred to play with others who exhibit the same behaviors as they do themselves (i.e. are similar to themselves).

There is support for this assumption: Jensen et al. [12] found that users are more likely to rely on information about similarity to other players than on reputation systems. Outside the field of online gaming this is corroborated by findings from social psychology [4]. We are more likely to get along with people who are similar to us on demographic attributes (e.g. age, education, and socio-economic status). Cooperation in face-to-face ad-hoc encounters is often ensured by exchanging personal background information, by looking for an overlap in personal history, and by establishing common ground [5].

For this reason we are eliciting not only the attributes individual gamers are seeking in others, but also those that they report about themselves. In this way we are able to establish whether the desirability and presence of specific behavioral attributes varies sufficiently within a socio-demographically homogenous population whose members are mainly interested in one-off encounters. If it exists and if similarity on these attributes is a decisive factor for gaming partner preference this condition would be met.

3. Research questions and approach

The goal of the study described in this paper was to identify how matchmaking for one-off gaming encounters could be improved with a view to reducing the occurrence of perceived "bad" behavior. The Xbox Live game MechAssault was chosen as the domain for the study, as one-off gaming encounters are typical for this game and as anecdotal evidence suggests a high number of unpleasant encounters. Two key research questions were addressed:

1. Are there differences in the behavioral attributes that individual gamers exhibit and prefer in others? And, if yes, can gamers be categorized in distinct types based on their attributes and preferences?
2. If distinct types exist, do they complement each other with regard to their exhibited and preferred attributes?

To answer the research questions and to create a blueprint for a matchmaking system we conducted a multi-stage study to elicit what we termed gamer attributes and relate those to gaming partner preferences. We based our analysis on explicit (e.g., self-reported age, self-reported preference for trash-talking) and implicit attributes; i.e. those that had to be inferred 'between the lines' from the overall profile (e.g., friendliness, socio-economic status). Importantly, we analyzed the choices participants made based on these profile attributes on an intra-individual level [19]. This means that we created a preference model that defined the configuration of attributes each participant used uniquely to choose gaming partners. We then clustered participants based on these personal preference configurations in order to define player types.

The contributions of this paper are thus twofold. (1) It describes a test for whether distinct behavioral attributes and preferences exist within an otherwise homogenous gamer population. If we find such variance even within the Mechassault population, the approach of intra-individual matchmaking is likely to be successful in many other contexts of online interaction where user populations exhibit more diversity. (2) A second contribution of this paper is to provide a case study for the identification of attributes relevant to matchmaking within a specific user population. While the attributes are unlikely to generalize, the approach described in this paper can be applied to other user populations and contexts of use.

4. Method

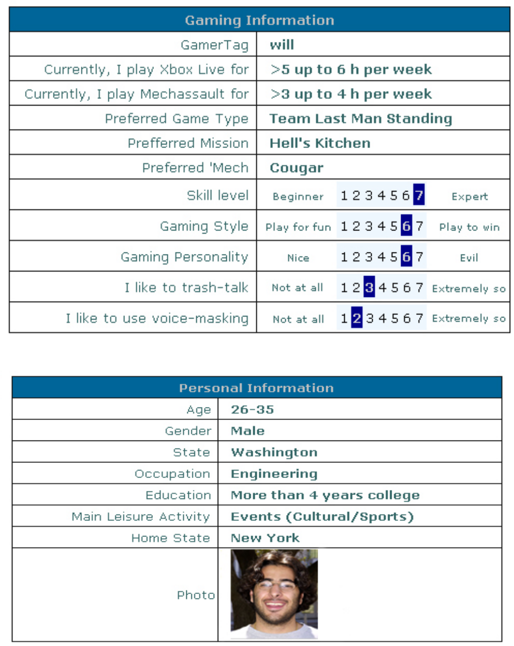
4.1 Overview

The study involved a four step process. First, relevant explicit attributes (e.g., preferred mission; Figure 1) for online gamer profiles were determined. Second, a set of real gamer profiles containing these explicit attributes were elicited from the gamer population to use as stimuli. During profile creation, each participant was randomly assigned to one of three types of profiles: *text-only, text & photo, and text & voice* statement profiles. (Background and a comparative analysis for these different media conditions is reported in [17]). Third, meaningful implicit attributes (e.g., trustworthiness, likeability; Table 1) of the profiles were determined and each profile was rated for the degree to which it contained these implicit attributes. Finally, a group of gamers rated the extent to which they would like to play with the players portrayed in their profiles. This methodology allowed us to connect each player's profile with other gamers' desire to engage in a game with that player.

4.2 Material

4.2.1 Creating Stimulus Profiles. We sent study invitations through email to 9309 gamers in the US who had played MechAssault online within the previous year. For this phase of the study we asked participants to visit a website we had set up and create personal profiles for themselves. As an incentive for creating a profile, we entered participants into a sweepstakes to win software titles. From the profiles that were completed and approved for inclusion in this study, we randomly selected 150 as stimuli for the main stage of the study.

4.2.3 Defining Profile Attributes, Explicit. Prompted by our review of the social psychology literature (see 'Background'), we decided to include explicit attributes that were specific to MechAssault as well as those that captured details about players' personal background. To define explicit gaming-specific attributes we conducted open-ended in-depth interviews with 7 gamers and a review of gaming community sites such as Gamertag.com. Several of the gaming attributes we identified give insight into expected in-game behavior (e.g. propensity for trash-talking or gaming personality). The explicit personal attributes we picked reflected those that are commonly available at online community sites such as MSN or Friendster and included age, main leisure activity and occupation (see Figure 1).



Gaming Information	
GamerTag	will
Currently, I play Xbox Live for	>5 up to 6 h per week
Currently, I play Mechassault for	>3 up to 4 h per week
Preferred Game Type	Team Last Man Standing
Prefferred Mission	Hell's Kitchen
Preferred 'Mech	Cougar
Skill level	Beginner 1 2 3 4 5 6 7 Expert
Gaming Style	Play for fun 1 2 3 4 5 6 7 Play to win
Gaming Personality	Nice 1 2 3 4 5 6 7 Evil
I like to trash-talk	Not at all 1 2 3 4 5 6 7 Extremely so
I like to use voice-masking	Not at all 1 2 3 4 5 6 7 Extremely so

Personal Information	
Age	26-35
Gender	Male
State	Washington
Occupation	Engineering
Education	More than 4 years college
Main Leisure Activity	Events (Cultural/Sports)
Home State	New York
Photo	

Figure 1. Sample gamer profile.

4.2.3 Defining Profile Attributes, Implicit. By combining information from individual gaming attributes participants could, infer additional information about a player's likely in-game behavior. Furthermore, particularly the profiles with photos and voice tags should carry much implicit social information (e.g. perceived intelligence, socio-economic status) beyond what could be expressed in individual explicit attributes. To identify underlying implicit attributes that would be relevant to gaming partner choice, we conducted focused interviews with 6 MechAssault players. We supplemented the resulting list of implicit attributes with those that are known to be predictors of preference (e.g. attractiveness [4]; see Table 1). As a next step we invited 16 MechAssault players to code the stimulus profiles on these implicit attributes. To keep the coding process within an acceptable time frame for our raters we randomly split the 150 profiles in two groups and had 8 raters code 75 profiles each. Table 1 reports how reliably the implicit attributes could be coded across coders within each group. We excluded Humorousness (12) from our subsequent analysis, as it showed very poor reliability (*intraclass r* < .7).

Table 1. Implicit attributes.

ID	Implict Attribute	Intraclass r (ICC)	
		Group 1	Group 2
I1	Honesty	0.75	0.70
I2	Team Player	0.71	0.70
I3	Committed Gamer	0.95	0.96
I4	Socio-Economic Status	0.86	0.90
I5	Intelligence	0.83	0.84
I6	Trustworthiness	0.75	0.72
I7	Enacts a Gaming Role	0.68	0.79
I8	Attractiveness*	0.74	0.71
I9	Friendliness	0.80	0.84
I10	Likeability	0.79	0.81
I11	Aggressiveness	0.86	0.84
I12	Humorousness**	0.38	0.32
I13	Trashtalker	0.96	0.94
I14	Rich Media Convey Personality***	0.92	0.92
I15	Rich Media Fit Other Information***	0.92	0.93

*Attractiveness (I8) was only reliably coded for voice profiles

**Humorousness (I12) was excluded from further analysis.

***Attributes I14 and I15 were only coded for photo and audio profiles

4.3 Participants

For the main part of the study we invited 516 participants who had submitted a profile in the previous step of the study to rate how much they would like to play with other gamers based on those gamers' profiles. We entered participants in this stage in a second sweepstakes. 267 participants that submitted a complete response set were included in the analysis. These participants were predominantly male (96%) and Caucasian (72%); confirming the homogeneity of the MechAssault gamer population. 66% had at least 2 years of college, and the age ranged from 18 to 71 (M = 29.7, SD = 8.4).

4.4 Measures

Our key dependent variable was preference. For each profile we asked "How much would you like to play MechAssault with this player?" Responses were recorded with a 7-point Likert scale (1: "Not at all" to 7: "Extremely So"). After they had rated all profiles we asked in an open-ended question which information participants cared about when picking gaming partners.

4.5 Procedure

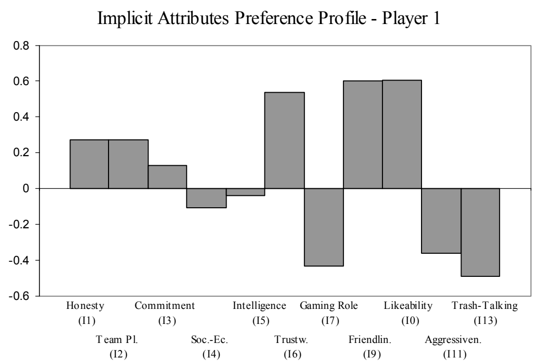
Participants logged in to the study website to view profiles and give their ratings. All participants rated two practice profiles to get familiar with the experimental system. Subsequently, they rated 50 profiles (in one of the three media conditions), one by one in randomized order. Participants whose profile had been selected as stimulus only rated 49 profiles. Participants could look at and rate each profile only once. Figure 1 shows a sample profile.

5. Results

5.1 Predictors of Preference

As a matchmaking system can only operate on individual differences in gaming partner preferences, we began our analysis on the intra-individual level. That is, for each individual participant, we assessed the impact of the different explicit and implicit attributes of the stimuli profiles on his preference response. To do so, we calculated a correlation term (Pearson) for each participant between his preference response and the profile attributes of the stimuli profiles. Values between 0 and 1 indicate a positive influence of an attribute on an individual participant's gaming partner preference. Values between -1 and 0 indicate a negative influence. Because these correlation values indicate the impact each attribute had on preference, we refer to them as impact scores. In turn, we call the overall configuration of these impact scores for each participant his *preference profile* (distinct from the gamer profiles used as stimuli, shown in Figure 1).

The preference profiles are unique to each individual and are often very different. For example, looking just at the implicit attributes, Figure 2 shows the impact of each implicit attribute on the gaming partner preference for two participants. It is apparent that Player 1 mainly sought to play with trustworthy (r = .54; I6), friendly (r = .60; I9) and likeable (r = .60; I10) players, while he avoided aggressive (r = -.36; I11) trash-talking (r = -.49; I13) ones. Player 2, on the other hand, was mostly interested in playing with a committed gamer (r = .62; I3) and showed clearly less interest in any of the other attributes.



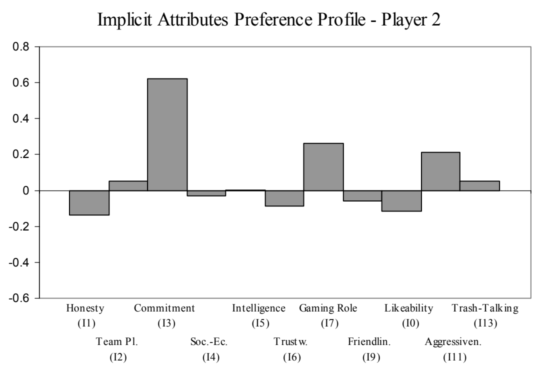


Figure 2: Comparing preference profiles.

5.1.1 Player Types. While we established that players are distinguished by unique preference profiles, we hoped to extract player types based on commonalities in the preference profiles, as these could be used to facilitate a simple, yet effective matchmaking system. To do so, we performed a hierarchical cluster analysis on participants' preference profiles and identified 3 meaningful types: *socially-oriented* players (46.4 % of participants), *skill-oriented* players (44.2 %), and *extreme* players (9. 4%, see Table 2 and Table 3).

Extreme players are characterized by a strong preference for aggressive gaming partners (r = .45) and those that describe themselves as trash-talkers (r = .34) or 'evil' (r = .33). Socially-oriented players on the other hand, avoid players with these attributes; rather they are interested in playing with friendly (r = .48), likeable (r = .48), and trustworthy players (r = .40). Skill-oriented players are mainly concerned about playing with highly skilled players (r = .18), and have less interest in the other attributes.

Tables 2 and 3 give an overview on the impact scores of all explicit and implicit attributes for these player types. One-way ANOVAs showed significant differences between the player types on all impact scores (i.e. the intra-individual correlations; p-values for ANOVAS are given in the tables). Exceptions were the explicit attribute Voice-Masking (indicating the likelihood of a players' use of the voice masking, i.e. distortion, feature of the Xbox Live service, see Figure 1 and Table 2) and the implicit attribute Personality Conveyed (I14, Table 3).

Table 2. Mean impact scores for explicit attributes by player types.

	Social	Skill	Extreme	p
	M *SD*	M *SD*	M *SD*	
Xbox Hours	-0.20 *0.20*	0.09 *0.20*	0.30 *0.17*	< .001
Mech Hours	-0.16 *0.22*	0.11 *0.21*	0.24 *0.15*	< .001
Skill	-0.33 *0.28*	0.18 *0.30*	0.45 *0.25*	< .001
Gaming Style	-0.30 *0.16*	0.05 *0.17*	0.30 *0.14*	< .001
Gaming Personality	-0.35 *0.17*	0.01 *0.15*	0.33 *0.12*	< .001
Trash Talking	-0.37 *0.17*	0.02 *0.17*	0.34 *0.17*	< .001
Voice Masking	-0.02 *0.16*	-0.03 *0.16*	-0.05 *0.18*	ns.
Age	0.14 *0.17*	-0.02 *0.16*	-0.20 *0.13*	< .001
Education	0.07 *0.17*	0.03 *0.13*	-0.15 *0.12*	< .001

Table 3. Mean impact scores for implicit attributes by player types.

		Social	Skill	Extreme	p
		M *SD*	M *SD*	M *SD*	
I1	Honesty	0.28 *0.17*	-0.04 *0.18*	-0.30 *0.20*	< .001
I2	Team Player	0.26 *0.19*	0.06 *0.18*	-0.23 *0.10*	< .001
I3	Committed Gamer	-0.26 *0.28*	0.11 *0.24*	0.42 *0.19*	< .001
I4	Soc.-Ec. Status	0.12 *0.19*	0.06 *0.12*	-0.16 *0.11*	< .001
I5	Intelligence	0.16 *0.21*	0.07 *0.12*	-0.22 *0.12*	< .001
I6	Trustworthiness	0.40 *0.17*	0.03 *0.16*	-0.31 *0.09*	< .001
I7	Gaming Role	-0.42 *0.17*	0.01 *0.17*	0.37 *0.11*	< .001
I8	Attractiveness*	0.48 *0.14*	0.13 *0.13*	-0.22 *0.09*	< .001
I9	Friendliness	0.48 *0.17*	0.02 *0.17*	-0.36 *0.12*	< .001
I10	Likeability	0.48 *0.17*	0.04 *0.17*	-0.35 *0.11*	< .001
I11	Aggressiveness	-0.45 *0.17*	0.07 *0.18*	0.45 *0.14*	< .001
I13	Trashtalker	-0.43 *0.17*	0.02 *0.18*	0.40 *0.18*	< .001
I14	Pers. Conv.**	0.09 *0.13*	0.05 *0.13*	0.04 *0.09*	ns.
I15	Rich Media Fit**	0.19 *0.14*	0.03 *0.14*	-0.13 *0.10*	< .001

* Attractiveness could only be reliably coded for voice profiles (Table 2)

** These attributes applied only to photo and voice profiles

5.1.2 Predicting Player Type. Summing up so far, each player is unique in his preference profile, but these profiles do contain enough similarity to cluster players into player types. Even if a matchmaking system was unable to utilize the finer details of a player's preference profile, if it could classify him into one of the three player types it might do a better job of matching him appropriately to gaming partners than present systems. The question remains, however, of how a system might collect information in order to make such a classification. One possibility is to have players rate mock profiles that are known discriminators of player type. A second possibility is that self-descriptions in player's own profiles correspond in a systematic way to the player attributes they prefer in others. As noted in section 3 ('Research Questions') this would be the case if gamers sought to play with others that exhibit similar behaviors to themselves.

Table 4. Differences between player types – self-described explicit attributes.

	Social	Skill	Extreme	p
	M	M	M	
	SD	*SD*	*SD*	
Xbox Hours	3.48	6.29	7.48	< .001
	3.79	*7.01*	*9.27*	
MechAssault Hours	7.09	12.72	16.20	< .001
	6.37	*13.12*	*16.15*	
Skill	3.59	4.87	4.76	< .001
	1.36	*1.44*	*1.39*	
Gaming Style	3.11	4.37	5.12	< .001
	1.67	*1.59*	*1.76*	
Gaming Personality	2.36	3.08	3.52	< .001
	1.22	*1.47*	*1.64*	
Trash Talking	2.42	3.22	3.76	< .001
	1.42	*1.63*	*1.51*	
Voice Masking	1.50	1.33	1.12	ns.
	1.28	*1.11*	*0.33*	
Age	30.83	26.77	25.72	< .001
	8.02	*6.28*	*7.81*	
Education	3.22	3.12	2.68	ns.
	0.98	*1.07*	*0.99*	

We investigated this possibility and found that players of different types (i.e. those with distinct types of preference profiles) also differed on their self-described profile attributes (with the exception of education and use of voice masking, see Table 4). Tukey's HSD pot-hoc tests (all $p < .001$) showed that socially-oriented players rated themselves as less skilled, as having a 'nicer' gaming personality, as having a less competitive gaming style, and as being older than skill-oriented and extreme players. Thus, socially-oriented players, who are distinct in their preference profile, also show a characteristic self-described attribute profile. Interestingly the socially-oriented players' self-descriptions reflect the attributes they seek in others (see Table 2). Hence, socially-oriented players seek to play with those that are similar to them on attributes such as trash-talking, gaming style, and gaming personality. These self-described attributes are likely candidates for use in matchmaking systems as proxies for preference. Post-hoc tests did not, however, show any significant differences in self-described attributes between skill-oriented and extreme players. These two types can thus not be distinguished from self-reported explicit attributes alone and it is unclear whether they themselves exhibit the qualities they are looking for in others.

5.1.3 Leveraging Self-Described Attributes. We found that it is possible to identify different player types based on their unique preference responses to a series of stimulus profiles. We also identified that socially-oriented players can be distinguished based on a small number of self-described explicit attributes alone and that they exhibit the attributes and behaviors they are seeking in others. This finding suggests that matchmaking based on self-reported gaming attributes alone could be a promising approach towards reducing perceived bad behavior in the MechAssault gamer population.

As an extreme example, we investigated whether a very simplistic matchmaking system with only one explicit attribute, could be reasonably successful. We conducted an analysis for the explicit attribute trash-talking, as it led to the most distinct preference distribution across the player types (Table 2). Could this attribute alone be used as a means of matching players with their preferred gaming partner?

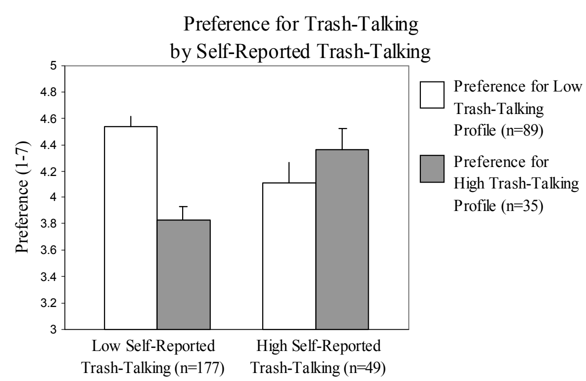


Figure 4. Preference for Trash-Talkers

We first differentiated between self-described low trash-talkers (responses 1-3; see Figure 1 for scales) and self-described high trash-talkers (5-7; neutral responders were dropped from this analysis). We then compared the mean preference responses these groups gave to profiles that we had also categorized as low and high trash-talkers. A repeated measures ANOVA with stimulus profile trash-talking level as within-subjects factor and players' self-described trash-talking level as between-subjects factor shows a significant interaction effect (F (1, 223) = 24.15, p < .001). Subsequent within-subject comparisons show that participants who describe themselves as rare trash-talkers prefer to play with those that rarely trash-talk (t (176) = 8.36, p < .001). This finding corroborates the previously reported result that socially-oriented players themselves exhibit the characteristics they are looking for in others.

For frequent trash-talking gamers, the relationship is inverse although the difference is not significant (t (48) = -.15, ns; see Figure 3). There are two potential explanations for this result. One is that frequent trash-talkers do not mind who they play with regarding their gaming partners' tendency to trash-talk. The other explanation is that frequent trash-talker players are made up of two distinct subgroups: those that seek other trash-talkers (i.e. those that have an extreme player preference profile; see Table 2) and those that have a socially-oriented preference profile, but do not exhibit the qualities they are looking for themselves. They may be a minority of aggressive players that look for non-aggressive players to spoil their game. Future studies will be required to resolve this question.

6. Discussion

Our research was motivated by two observations. First, many of the established approaches towards ensuring compliance with established norms of behavior seem to be unsuccessful in the one-off encounters that are typical for many online gaming platforms, resulting in unsatisfying gaming encounters. Second, the literature suggests individuals may differ in the behavioral attributes they exhibit and seek in others. These observations indicate that matchmaking based on complementary social and behavioral attributes and preferences could be an approach to improve perceived norm-compliance. However, little research exists into the existence of such distinct groups for online environments that largely cater for one-off encounters. We investigated this approach for the MechAssault gaming population.

We addressed two specific research questions. (1) Are there individual differences in gamers' exhibited and preferred behavioral attributes (i.e. distinct preference profiles) and, based on these individual differences, are there distinct preference types? (2) Could these types be the basis of successful matchmaking (i.e. is there a match between preferred and exhibited behavior within the gamer population)? Our reasoning was that much perceived misbehavior may not be the result of intentional norm violation, but of a mismatch of individuals with differing norms.

6.1 Predictors of Preference

To answer the above questions, we investigated which explicit and implicit attributes determine gaming partner choice. We were particularly interested in attributes to which participants exhibited a differential preference response as these are promising candidates for inclusion in a matchmaking system.

First we conducted an analysis on the intra-individual level that showed each player carries a unique preference profile marking the profile characteristics he finds desirable and undesirable. These profiles not only differentiate each gamer, but they quantify the degree to which specific elements of other gamers' profiles impact partner preference. While these preference profiles could be extremely useful in the matchmaking process, they are complex, consisting of a fairly large number of items that may be hard to capture in a gaming system.

As a first step to simplification we clustered members of the sample population into three player preference types: social, skill, and extreme. By correctly categorizing users into preference types, a system should be able to significantly improve its matchmaking. It is important to note that we identified these particular types for the MechAssault gamer population. Hence, these specific types may not generalize to other gamer populations or other contexts of use. The fact, however, that distinct types were found even within this homogenous population, suggests that distinct types can also be identified in other more diverse populations using the process we describe in this paper.

We also found a relationship between self-reported attributes and player preference type. Hence, within the MechAssault gamer population a categorization could be accomplished with reasonable success, especially for separating socially-oriented players, based on a handful of self-report items in the absence of a more sophisticated system capable of utilizing a player's full preference profile. Again our findings within one specific gaming environment bode well for similar approaches in other contexts where instant matches for one-off interactions are prevalent and perceived norm-violation could be problematic: online chat support groups, online dating, or file and resource sharing.

6.2 MechAssault Player Types

Describing the specific gamer types identified in the MechAssault population, we found that skill-oriented players did not care about the cooperativeness or the personal attributes of other gamers. They were mainly interested in finding players with a high skill level. They closely map to the 'Achiever' type described by Bartle [2] based on qualitative observations in MUDs. Present matchmaking services, which tend to focus on technical game aspects and skill level, thus cater to players of this type.

Socially-oriented players, on the other hand, were mainly concerned with playing with others who are likeable, friendly, and do not enact a gaming role that could be perceived as threatening. Interestingly they themselves exhibited these characteristics in their self-described profiles. One participant's statement after having selected potential gaming partners (step 4) illustrates this:

"Age also makes a bit of a difference. At age 35, I typically do NOT want to play with an expert 15 year old that just got home from school."

Hence, for socially-oriented gamers our findings support the notion that similarity on personal attributes is a good predictor for gaming partner choice [4], [12].

Somewhat paradoxically, extreme players also were impacted by personal attributes of other gamers, although in the opposite direction of social players: cooperative attributes were seen as undesirable, and aggressive attributes as desirable. This is probably the most important finding regarding the use of matchmaking for reducing perceived "bad" behavior. It suggests that within the MechAssault gamer population there is indeed a sub-population with a demand for behavioral attributes that are seen as undesirable by the majority. In other words rather than trying to remove such behavior by utilizing norm-compliance enforcing mechanisms (e.g. policing), a system could match demand for these characteristics with supply; i.e. match aggressive players with those that prefer an aggressive playing style.

6.3 Preference and Behavior Archetypes

The similarity between the player preference types that emerged in an analysis of the MechAssault population and Bartle's qualitative description of player types in MUDs suggests the existence of gaming partner preference archetypes: preference patterns that exist across a wide range of gaming contexts and types of interactions. We found similarity in types between MUDs and MechAssault, an arcade-type game. The former facilitates long-standing relationships among players and supports the emergence of distinct player sub-cultures, while the latter typically facilitates one-off encounters. This similarity in findings across different types of populations advocates further research into the existence of such archetypes of behavior and preference across gaming platforms, but more importantly, also across further contexts of online interaction. If such archetypes are found, matchmaking systems that cater to them could emerge as a very successful approach towards improving perceived behavior across many application contexts. A next step into this direction would be to conduct a meta-analysis of the data collected by Ducheneaut et al. [9] in MMORPGs and to review our data against Sherry's analysis of aggressive gameplay [19].

7. Conclusions

Using our experimental matchmaking system we analyzed gamers' self-described attributes as well as gaming partner choices for MechAssault, an Xbox Live game that typically supports one-off encounters and has a gaming population that is relatively uniform in terms of socio-demographic makeup. Even within this population we identified player types with distinct preference patterns: skill-oriented, socially oriented, and extreme players. While these specific types may not generalize to other gaming populations or contexts, they indicate that there is no universally agreed definition of appropriate in-game behavior. Gamers differ in the behaviors they exhibit and seek. For the gaming domain these findings suggest that matchmaking is a more promising approach to reducing occurrences of perceived bad behavior than enforcing uniform behavioral standards. Future studies will have to test how this finding transfers to other domains of online interaction (e.g. online support or online dating systems).

The player preference types (social, skill, extreme) we identified in this study are specific to the MechAssault population. Hence, our hope is that the analytical approach of differentiating users based on their unique attributes and preference response patterns, which we demonstrated in this paper, can be used in other user populations and other contexts of use. However, we also noted a similarity to existing gamer typologies in MUDs, which support repeated encounters. Hence, investigating whether there are archetypes that exhibit and expect specific behavioral attributes across application contexts is an interesting question for future research.

Many of the important attributes that helped define preference profiles were what we called implicit attributes (e.g. perceived intelligence, socio-economic status) that were conveyed in the overall gestalt of the profiles. In practice, collecting these attributes presents a challenge, and yet, responses to the implicit attributes frequently differentiated players and thus would be a boon to matchmaking. Our suggestion to practitioners is to utilize targeted self-report items such as level of trash-talking, while designing a long-term solution that integrates the implicit attributes. Implicit attribute ratings might be collected by the system over time through post-game player feedback or by analyzing in-game behavior.

With regard to the research agenda in CMC and CSCW our findings encourage broadening the focus beyond systems that support norm-compliance towards systems that allow the co-existence of distinct behavioral norms. After all, online communities are not subject to the many constraints of face-to-face groups, where truly distinct behavioral norms may not be tolerable in close proximity. So, rather than aiming to recreate these constraints, researchers should also look for solutions that render them obsolete.

8. References

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