The Social Behaviors of Experts in Massive Multiplayer Online Role-playing Games

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***Abstract*— We examine the social behaviors of game experts in Everquest II, a popular massive multiplayer online role-playing game (MMO). We rely on Exponential Random Graph Models (ERGM) to examine the anonymous privacy-protected social networks of 1,457 players over a five-day period. We find that those who achieve the most in the game send and receive more communication, while those who perform the most efficiently at the game show no difference in communication behavior from other players. Both achievement and performance experts tend to communicate with those at similar expertise levels, and higher-level experts are more likely to receive communication from other players.**

Games; communication systems; networks; social factors

I. INTRODUCTION

Massively multiplayer online role-playing games (MMOs) continue to grow at an unprecedented level. The player population of the most popular MMOs ranges from 70,000 to 10 million. The sheer popularity of these games merits interest; however, perhaps more compelling is the level of social interaction the virtual environments facilitate for users [1]. They involve complex social behaviors including collaborating on difficult tasks, trading and participating in an in-game economy and leading teams through the completion of a variety of quests, dungeons and raids. However, we know little about the social behaviors of those considered 'masters' of the game — the game experts.

The purpose of this paper is to examine the social behaviors of game experts in MMOs. We ask, do game experts socialize more frequently than non-experts? Do they chat with other experts? Do people seek out experts in these games? In order to answer these questions, we identify the chat networks that players engage in over a five-day period, and examine the extent to which high achievers and high performers socialize during their playtime. In this charge, we make a contribution by developing a theoretical understanding of expertise and social interaction in online games. Second, we rely on a unique data set that allows us to examine classical notions of expertise in large-scale online networks. Third, we make a methodological contribution by showing the utility of using Exponential Random Graph Models (ERGM), an advanced social network modeling approach [2], to describe social interaction patterns in large-scale online networks.

II. CONCEPTUAL FRAMEWORK

A. Defining Game Expertise

In order to examine the social behaviors of game experts, we must first conceptualize what constitutes an expert in offline settings. Generally, researchers define expertise as "high, outstanding, and exceptional performance which is domain-specific, stable over time, and related to experience and practice" [3]. More recently, scholars have added a social dimension to expertise, finding that experts demonstrate superior communication skills [3], which is especially important in team-based environments. Although video game expertise represents a unique setting, many of the qualities associated with expertise in real-world teams and organizations are applicable. In organizations, expertise is typically conceptualized in terms of "excellence" and "experience" and commonly associated with knowledge, problem-solving skills, goal setting, feedback processing, communication and cooperation [3]. These conceptualizations and attributes work well in MMO settings due the combination of task-oriented and social activities.

In MMOs, the primary objective is to complete quests and defeat monsters, which award adventurers with experience points and treasure. Characters gain levels through their accumulation of experience, which typically involves a level cap (level 70 in this case). These levels are visible to all other players. The levels that characters attain can be represented in terms of *achievement*. However, it represents a crude type of "meta-expertise" [4] equivalent to knowing a person's current job position or status without understanding the way they attained it. In other words, the 'process' of achieving expertise is equally important.

Therefore, we propose a second potential dimension by which we can characterize expertise: *performance*. It is plausible that any individual, given the right amount of time playing the game can reach the highest level. In effect, high achievement may largely be a function of time spent engaged in an activity. Yet time also serves as a viable control for understanding how *efficient* a player is in attaining the highest levels. For example, if Player A spends ten hours to reach level 10 and Player B spends 2 hours to reach level 10, we would surmise that Player B is performing more efficiently, and perhaps, *better* than Player A. Therefore, we consider game expertise along both dimensions: those who are able to achieve the most in the game; and those who are able to do so in the most efficient manner.

In real-world practices, experts have been distinguished in terms of "excellent performance", in which they demonstrate a superior ability to complete a set of tasks [3]. These studies show that experts spend less time solving complex problems, possess more tacit or procedural knowledge, and are better at setting goals and attaining them [3]. Especially important to our work, excellent performers are found to engage in more cooperative activities and communication with peers. However, it is still unclear the extent to which social behavior impacts achievement or performance.

B. Understanding Social Behavior

Recent studies show that experts in organizations are more sociable than their counterparts. For example, experts are more cooperative, demonstrate a higher frequency of communication to and from their peers or subordinates, and are generally more "socially skilled" [3]. Being social allows experts to spread their knowledge, to capture information from their peers, or even direct the tasks of the group and improve its overall performance.

MMOs are often touted as being social spaces [5], although some research shows that users don't always take advantage of cooperative opportunities [6]. In fact, MMOs are unique from other games not only in content or the vastness of the worlds they present to players, but also in the expansiveness of their communication channels. Players can broadcast messages to the entire area (e.g., to offer up trade skills or to make a joke), to a particular team (e.g., to give directions in a five-person collaboration attempting to complete a dungeon) or directly to another player (e.g., to send a private message). Usually the chat system is integrated directly into the user interface of the game, and many of the more difficult encounters or activities that require players to form teams would be insurmountable if users did not communicate.

The extent to which game experts utilize these chat features to accomplish game goals is not clear. It could be that experts use chat to give directions or share valuable information, but it could also be the case that game experts focus on game tasks and 'listen' more than 'talk'. However, given the previous research on the sociability of experts, we would expect them to be more communicative than their counterparts (H1).

Even so, a second question remains regarding with whom experts are likely to chat. In interdependent group settings, where individuals must rely on others to complete tasks, people will often seek experts for their unique knowledge or ability [7] so it would be expected that lower-level, or inexperienced players might seek out game experts to learn about important locations in the game (e.g., a repair shop, merchant, or quest-giver), or strategies for defeating a particular monster (H2a and H2b). However, experts are probably more likely to interact with other experts, a concept found in network theories of homophily which states that people with similar characteristics are more likely to connect with one another (H3) [8]. Taken together, we hypothesize the following:

H1: Experts are more likely to send out chat messages than non-experts.

H2a: Experts are more likely to receive chat messages than non-experts.

H2b: Higher-level experts are more likely to receive chat messages.

H3: Characters at similar expertise levels are more likely to exchange chat messages with each other.

III. METHOD

A. Sample and Procedure

We rely on a sub-sample of one game server from the population of Sony's Everquest II (for a game overview, see http://everquest2.station.sony.com) that logged on between September 5, 2006 and September 9, 2006 and sent at least one chat message to another player. Although we do not know the gender and age composition of these players, the character gender was available (male = 946 (64.9%); female = 511 (35.1%) which is close to the character gender makeup found in other studies [9].

In order to capture the communication, we rely on user logs, which capture all incoming and outgoing private chats in the game. These logs do not capture the content of these messages, only the source and targets, and the user names remain anonymous. The in-game chat system takes up the lower-left hand quadrant of the user interface and allows players to type messages to the other players they are grouped up with, to entire towns or cities, or as a private message to an individual player (which only the recipient can see). All communications were captured on the Sony database, along with the date and time they were sent and received. We identified the senders and targets of all private messages and constructed a socio-matrix for use with the social network tools described below. In order to reduce the social network to a reasonable size for our statistical tools, we dichotomized links

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at the average frequency (i.e., 11), which resulted in 1,457 participants.

In addition to the communication logs, we also rely on a separate user log that collects the experience gained for completing quests or killing monsters. However, the experience logs and communication logs only allow a five-day overlap in our data collection, which is why we utilize this time duration in our sample.

B. Dependent Measures

1) Achievement Expertise

We measure achievement expertise as the accumulation of experience points over the five-day period for each user. Characters receive experience when they defeat a monster or complete a quest, so users can level their characters by repeatedly killing monsters (known as 'grinding'), or by completing quests or dungeon adventures, which sometimes require teams. Experience points are connected to character levels and higher levels require more experience points in a curvilinear fashion; therefore, higher-level players tend to receive more experience points for completing quests and killing monsters. In order to keep all variables on a similar scale, we divided the achievement score by 1000 and rounded the value to a final integer.

2) Performance Expertise

Because it is possible to accumulate experience points achievement over time, we also include a measurement of expertise that controls for time. We measure performance expertise by taking the achievement score and dividing it by the total play time (in hours) over the five-day period.

C. Independent Measures

1) Expert-initiated Chat

We define expert-initiated chat as the probability that a chat link will be sent from an expert.

2) Expert-targeted Chat

We define expert-targeted chat as the probability that a chat message will be directed toward an expert.

3) Directed Chat

We also calculate the group-level likelihood that players send out chat messages to other players in the community.

4) Mutual Chat

We also calculate the group-level likelihood that players who send a chat message will receive a reciprocal message.

5) Chat based on Expertise Difference

This is calculated as the character level gap between any two players and represents the likelihood that communication will occur between two players at similar or dissimilar levels.

6) Level

We identify the character level of each player, which ranges from 1-70. This serves as a control variable.

7) Expert-targeted Chat (Level)

This variable takes into account the level of the expert and represents the likelihood that a higher-level player is more to receive chat messages from others.

8) Time Playing

We also collect the amount of time (in hours) that a user logged onto the game during the five-day period, which was then used to calculate the performance measure of expertise. The five-day period began on Tuesday, September 5 (at midnight) and ended on Saturday, September 9 (at midnight).

IV. Results

A. Descriptive Statistics

The means, standard deviations and ranges of all variables of interest are listed in Table 1.

TABLE I. MEANS, STANDARD DEVIATIONS AND RANGE OF VARIABLES OF INTEREST

Variable	Mean	SD	Min	Max
Achievement	85,929	106,858	183	896,136
Performance (per minute)	160.95	232.33	0	6375
Character level	47.08	17.98	1	70
Incoming Communication	51.34	84.48	0	1252
Outgoing Communication	51.44	23	0	1378
Play time (hour)	10.70	11.97	0.003	108.05

B. Network Analysis Model Summary

The network data used in this study pose considerable analytic challenges, which call for a sophisticated network analysis approach. Traditional statistical techniques assume that observations are independent. However, an observation about a network link is not independent of the other links. In other words, the communication between any two players may be influenced by their communication with other members of the game, or by the general communication patterns of the group as a whole (e.g., most people communicate *versus* very few people communicate; people link to many others *versus* a sparse network of communication). Although the lack of independence in network data has been widely recognized [10], researchers have often resorted to using traditional statistical techniques due to the lack of appropriate analytic techniques until recently.

This study addresses this methodological weakness by employing a recently developed set of techniques called Exponential Random Graph Models (ERGM) or *p** models [11]. ERGM offers an opportunity to explain networks based on multiple levels of analysis. This includes communication from the individual, within dyadic and triadic relationships, and from an overall group perspective (i.e., the connectedness or sparseness of all players in the game).

This study uses the program *Statnet*, developed by Handcock and colleagues [12] in order to measure two stages of ERGM network structures. The first is parameter estimation, which employs Markov Chain Monte Carlo maximum likelihood estimation (MCMCMLE) [2, as recommended by 13]. This method provides more reliable standard error estimates, although there may be difficulty in reaching converged models.

The second step is the diagnostic *Goodness of Fit* (GOF) examination. Once the parameter estimates are obtained from the observed network, a large number of networks are simulated based on these estimates. If the estimates accurately capture the structural characteristics of the observed network, the observed network should be very likely to occur within the distribution of simulated networks. If the estimated model does not fit the observed network well, the observed network will have a much lower probability of occurring in the distribution of simulated networks. A degeneracy value below or close to 1 indicates good convergence, while a value approaching 20 indicates a problem with convergence [14]. Models with Goodness of Fit statistics below 2 are considered as good fits of the data.

C. Achievement Experts

As shown in Table 2, the *Achievement Model* is a good fit and reaches convergence (*degeneracy value* = .10). There is a significant relationship between directed chat (*Estimate* = –8.28, *SE* = .04, *p* <.001, *GOF* = 0.92) and achievement expertise. This variable represents the communication patterns of *all* players of the game and shows that generally speaking, players are less likely to communicate with other players. There is also a positive and significant tendency for mutual chat (*Estimate* = 8.61, *SE* = .09, *p* <.001, *GOF* = 0.96), which suggests that if players do send a chat message to another player, they are likely to receive reciprocation.

We predicted that experts would initiate more chat communication (H1) and serve as the targets of more chat communication (H2a). These hypotheses are supported. There are significant and positive effects for *expert-initiated chat* (*Estimate* = 0.002, *SE* = .0003, *p* < .001, *GOF* = 0.54), and *expert-targeted chat* (*Estimate* = 0.002, *SE* = .0003, *p* < .001, *GOF* = 0.22), and achievement expertise when controlling for other structural effects. Therefore, achievement experts are more likely to send out and receive chat messages than non-experts.

Our hypothesis that higher-level experts would receive more chats (H2b) is supported. There is a positive and significant effect for *expert-targeted chat (level)* (*Estimate* = 0.004, SE = *p* < .001, *GOF* = 0.50) and achievement experts. Therefore, higher-level experts are more likely to receive chats from other players.

We also predicted that experts would communicate with other players at similar levels (H3). This hypothesis is also supported. There is a significant and negative effect of *chat based on expertise difference* (*Estimate* = –0.002, *SE* = .0001 *p* < .05, *GOF* = 0.44) on achievement experts. Therefore, people are more likely to send chat messages to those at similar expertise levels.

D. Performance Experts

As shown in Table 3, the Performance Model is a good fit and is very close to convergence (*degeneracy value* = 1.08). There is a significant relationship between directed chat (*Estimate* = –8.18, *SE* = .05, *p* <.001, *GOF* = 0.82) and performance expertise. There is also a positive and significant relationship between mutual chat (*Estimate* = 8.64, *SE* = .09, *p* <.001, *GOF* = .80) and performance expertise. Again, this shows that the general community of players does not usually attempt to chat, but when they do, they are likely to experience reciprocation.

TABLE II. SUMMARY OF ERGM RESULTS FOR ACHIEVEMENT MODEL OF GAME EXPERTISE

Variable	Estimate	Std. Error	GOF
Directed chat	–8.281***	.0438	.92
Mutual chat	8.609***	.0849	.96
Expert-initiated chat	.002***	.0003	.54
Expert-targeted chat	.002***	.0003	.22
Expert-targeted chat (level)	.004***	.0002	.50
Chat based on expertise difference	–.002***	.0001	.44
Degeneracy value	.096		

Note: ***p<.001.

When measuring expertise in terms of performance, which includes the amount of time that players log onto the game, our first and second hypotheses are no longer supported. Neither *expert-initiated chat* nor *expert-targeted chat* show significant effects (*p* = .90 and *p* = .31, respectively). In other words, performance experts are not significantly different in sending or receiving chat messages than non-experts.

However, higher-level performance experts were more likely to receive chat messages (H2a). There is a positive and significant effect for *expert-targeted chat (level)* (*Estimate* = 0.005, *SE* = .0002, *p* < .001, *GOF* = 0.26) and performance expertise, which shows that players seek out higher-level experts. Likewise, our third hypothesis is supported. The effect of *chat based on expertise difference* was significant and negative (*Estimate* = –0.001, *SE* = .0002, *p* < .001, *GOF* = 0.86). Therefore, characters are more likely to send chat messages to those at similar expertise levels.

TABLE III. SUMMARY OF ERGM RESULTS FOR PERFORMANCE MODEL OF GAME EXPERTISE

Variable	Estimate	Std. Error	GOF
Directed chat	–8.185***	.0510	.82
Mutual chat	8.641***	.0862	.80
Expert-initiated chat	.0000	.0002	.56
Expert-targeted chat	.0002	.0002	.76
Expert-targeted chat (level)	.0045***	.0002	.26
Chat based on expertise difference	–.0005***	.0001	.86
Degeneracy value	1.08		

Note: ***p<.001.

V. DISCUSSION

The purpose of this paper was to examine the social behaviors of game experts, or those who achieve the most in the game and outperform other players. We utilize the chat behaviors of players of an MMO to identify their communication networks and examine differences between incoming and outgoing chat messages, and communication preferences. The findings show that achievement experts and performance experts exhibit different communication behaviors, but both types tend to communicate with players of similar character levels, and both are sought after by other players based on their expertise. Achievement experts, who represent the amount of experience points they accumulate, are more likely to initiate and receive chat messages in the game. Performance experts, who represent how efficient a player accumulates these experience points, did not differ from other players in their frequency sending and receiving chat messages. In effect, game experts may generally be social creatures, but those who are most efficient at leveling their characters spend less time chatting with others.

The findings suggest that social interaction helps game players achieve more, but communication takes time and energy and can serve as a distraction from pure task-oriented activities. For example, every second used typing out chat messages rather than pushing the keys for spell-casting rotations would be considered "wasted" in terms of experience accumulation. Therefore, we can think of performance expertise as *game focus*. Those who are efficient at gaining experience points are task-oriented and primarily focused on the game activities such as completing quests or killing monsters more so than chatting with peers.

A second explanation is that performance experts do not need to chat with other players because they already know the answers. That is, chatting is not instrumentally necessary; performance experts do not need to seek out advice for defeating a particular monster or finding a location because they already know what to do or where to go. Likewise, they do not need to spend time coordinating efforts because they already know their role on the team and how to execute it flawlessly. In this, we can think of performance expertise as *game knowledge*. Those who are efficient at gaining experience points do not need to seek out information or feedback because they already have sufficient knowledge of the game.

Equally interesting is the finding that players send messages to higher-level experts. Research in real-world settings suggests that people seek out experts for advice and information, and our findings show this is reflected even in large-scale virtual worlds, and when players don't necessarily know each other. Since many aspects of MMOs involve strategy (to kill a certain boss), secret locations (to find a particularly important item or non-player character), or character customization (best gear and talent selection), it is understandable that players would seek out experts for advice.

This may also serve as an example of transactive memory theory, which posits that the knowledge of the collective exceeds that of any individual component and consists of processes such as expertise recognition, information allocation and retrieval and directory updating [8]. In the MMO environment, players recognize experts based on their achievement and performance, and they may be requesting information as previously described. They may also be providing information for future retrieval (e.g., 'where did I tell you that quest giver was again?').

Likewise, it's interesting that experts tend to communicate with players of similar levels. There are a couple explanations for this. First, players at the same level are likely to be more appealing to interact with than a low-level player because they share a similar set of experiences. Their mutual status suggests that they have braved the same dark dungeons, completed the same challenging quest lines, and perhaps spent the same amount of time in the game. They've learned the lingo, they know the maps, and they should play with the same ability. In other words, there is a certain amount of *perceived* expertise derived from seeing the same character level.

A. Implications for Social Computing in Virtual Teams

The findings also contribute to our broader understanding of social computing in virtual teams. Many argue that communication in virtual teams are constrained when compared to face-to-face settings, affecting the overall performance of the team; however, the development of relational ties can overcome these difficulties [15]. In fact, communication has often been the central focus of research on virtual groups [16]. Research suggests it is in the best interest of individuals to develop relational ties in order to increase their own personal achievement in virtual settings that involve collaboration. Our findings confirm that sociability is positively related to overall achievement, even in large-scale virtual networks.

Yet the finding that task performance is not enhanced by communication indicates that being social is not always beneficial. This in line with literature that shows that increasing the size of task groups can result in greater process loss [17] and social loafing [18] that decrease contributions of individuals and thus potential performance. Furthermore, the distance, greater anonymity, and reduced interaction cues of distributed teams all may increase the likelihood of coordination costs among those who interact [19]. Experts in virtual teams may experience diminishing returns in the benefits that they derive from social interaction with their peers. They are perhaps better served by being selective or strategic in their choice of social interaction partners or their frequency of communication. Additionally, managers of virtual teams may want to vary the level of social interaction required of group members for particular tasks. Lastly, it is important to recognize that evaluations of achievement and performance are a function of context. In our analysis of an MMO environment we were concerned with points amassed through specific task completion. In other interactive online environments, such as project teams, or social groups, evaluation may not be as rigid and task-dependent and therefore communication network size may have different effects.

Our findings do not suggest that communication is a bad thing, or that virtual teams should work in silence. Rather, we show that communication might serve as a distraction in task performance. It can very well (and does) serve to increase the satisfaction that one experiences in a virtual organization or community. However, it also divides one's attention when it comes to efficient task completion. Bowers, Braun & Morgan [20] provide evidence that virtual and non-virtual action teams perform worse when they have to communicate; however, it is unclear whether communication actually degrades performance or whether they have to communicate because they are running into performance problems.

B. Limitations and Future Work

One limitation of our findings is that higher-level players tend to use Voice-over-Internet-Protocol (VoIP) applications such as *Ventrillo* or *TeamSpeak* in order to utilize real-time voice chat in addition to in-game text chat [21]. This supports our intuition that difficult encounters in the game would require coordination through some level of communication. Certainly no player could compete in raids (i.e., end-game content that requires 10 to 25 players to form a team to enter) or challenging dungeons without some level of direction to coordinate activities.

In our future work, we plan to examine the relations between game expertise and specific game activities such as trading with other players, or engaging in player-vs-player (PVP) tasks. Second, we plan to incorporate other forms of chat (i.e., broadcast and party chat) and investigate whether differences between achievement and performance experts persist. Additionally, we will test for changes in expertise and communication over longer periods of time, which might indicate signatures of learning among players, and better inform the 'process' of becoming a game expert. Finally, we plan to explore more deeply whether game focus and game knowledge as an explanation for why performance experts spend less time socializing.

In conclusion, our findings suggest that undivided attention on tasks and game activities can improve one's efficiency in leveling and performance. However, chatting with other players or team members appears to generally be a common activity for game experts, even at the cost of pure performance. Therefore, MMOs—and virtual teams at-large—offer many compelling distractions in terms of social activities. As previously surmised, experts remain social creatures, even in virtual settings.

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