

# WHO GETS MORE BENEFITS FROM VIRTUAL COLLABORATION? QUANTITATIVE ANALYSIS ON THE PRODUCTIVITY FROM TEAM WORKS IN AN ONLINE

*Completed Research Paper*

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## **Abstract**

*There have been many studies on the collaboration of virtual teams using information communication technologies. However, few studies can be found on the collaboration where the productivity of individual users is assessed by secondary data other than primary data generated by survey methods. By using a data set from an online game, we quantitatively measure the productivity of team members in gaining experience points in the game. From our analysis, we find that a) the collaboration of online gamers by forming parties make the productivity of low level players much higher than that of high level players. Meanwhile, the high level players seem to gain some indirect benefits other than the experience points from the collaboration. b) The information centrality for better performance is crucial when applying social network analysis to our online servers and channels data in a small team network. It validates that Freeman's approach positively contributes to productivity. c) Leisure plays a key driver to make better productivity and virtual team size should increase for the intensive work in order to make better performance. Our quantitative measures are expected to provide some insights for better management of virtual worlds which become an important part of economy in real world.*

**Keywords:** cognitive load, information flow, social network, team productivity, virtual world

## Introduction

In turbulent business environments, many business units rely on diverse set of evenly distributed information recourses through virtual teams because effective information sharing among team members in virtual teams is important for establishing and sustaining competitive advantage (Teece et al. 1997). However, effective information coordination between members is more difficult in virtual teams than in traditional teams in business units due to temporal and spatial separation among team members and communication without face to face (Lewis 2004). Thus, the collaboration of information sharing between virtual team members is a central issue in understanding how virtual teams perform and develop (Cramton 2001). However, how information is shared for collaboration in virtual team and how the information collaboration impact on virtual team's productivity is little known. Another central issue is related to the measure of team productivity. A study exemplifies the measurement of team performance based on an objective measure provided by a simulation game. The accuracy of the objective measure is dependent on how the model built-in the simulation game closely represents the business units works (Kanawattanachai and Yoo 2007).

In our study, we quantify the productivities of online gamers by measuring the increased experience points<sup>1</sup> in a virtual world, an online game, and see how the collaboration among online gamers can contribute to increasing the experience points. From economic perspective, we employ Solow production function model in order to estimate virtual team performance because the model is widely used in the business unit context for measuring output efficiency. The increased experience points are positively associated with time and use of items efficiency obtained from concise estimations with the production function model.

The modern multimedia games are very similar to the virtual environment developed for other application domains because it provides another means of simulating real or imaginary world places and activities (Manninen 2001). Online game market has grown with enormous speed all around the world. The worldwide online game revenues and output value have reached US\$ 5.2 billion in 2006 and the game market will be forecasted to grow US\$ 13 billion by 2011 due to the increases in broadband households, higher PC penetration and more connected console video game systems (DFC Intelligence 2006). Online games are not merely software application because they are usually seen as a space with complicated dynamics of social interactions unlike general offline computer games or networked game with limited numbers of players (Ang et al. 2007). The games provide many opportunities for short-term relationship experience. For example, new gamers can team up with other players to perform the offered quests in order to develop the abilities of their avatars<sup>2</sup> or advanced gamers can help the new players to get through the game. Those are online communities mediated with computer mediated communication (CMC) tools. The communities play a very important role in facilitating social interactions in computer games. And an online team community is particularly multidisciplinary in nature (Preece et al. 2002). It is designed in a way that most players have to rely on others to complete certain missions or quests. This encourages the gamers to work together and join in a virtual team or communities because playing the game alone is less rewarding or less progress (Ang et al. 2007). The gaming situation induces new gamers to take part in a virtual team or communities. The games provide also opportunities for long-term relationship experience. Most players in the game seek more than merely strategic considerations when they interact with other players. That is, the players search for communication and persistent social relations (Ducheneaut and Moore 2004; Kolo and Baur 2004). However, Nova (2002) states that one problem in the game is the awareness<sup>3</sup> in virtual social spaces. In some populated spaces, the gamers are not aware of the activities and presence of other players and this could result in breakdown in social interaction. Another problem in the game is the lack of social play. The interaction in the game is instrumental rather than social (Harrison et al. 1993). Most players have short interactions in order to satisfy their needs. For example, when their needs are met, they leave the place to seek other goals. Although there are some players who interact genuinely with other players for the sake of socializing, such interaction is usually not rewarded by the game. That is, merely engaging in social play does not help processing in the game (Ang et al. 2007). The gaming situation induces the advanced players to leave the virtual team. The different level gamers gain access to information through cyber social network and CMC tool

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<sup>1</sup> a unit of measurement to quantify a game player's progression

<sup>2</sup> The graphical representation of the game user or character in games or virtual worlds: it is usually a three-dimensional form

<sup>3</sup> The knowledge of presence of other people, including their interaction and other activities

(Information Technology) in order to diminish cognitive loads in online games. This paper studies information flow and IT value to understand how the information sharing via social network affects the team productivity in virtual world.

### ***Cognitive load***

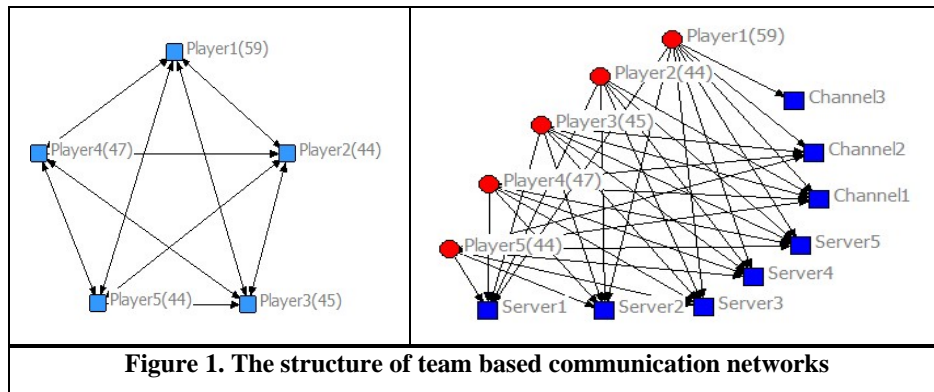
Cognitive load is often referred to as the amount of mental energy required to process a given amount of information (Feinberg and Murphy 2000). Sweller (1988) states that learning can be enhanced by the presentation of information by assuming a limited working memory. The major factor that contributes to cognitive load is the number of elements that need to be attended to (Sweller 1994). Two different levels of cognition exist in the game. For example, high cognition level has low capacity; the gamers can only handle one thing at a time, while on a low cognitive level the players can handle a number of familiar tasks. A task can be transferred from high to low level cognition by repetition. It will require very little effort and will be performed rapidly through the transfer (Godstein 2005). Online games requires a large number of game objects of performing quests, managing item inventory, equipping character, etc. These interactions, when carried out separately, do not cause cognitive load to new gamers or advanced players. However, in most cases, these actions need to be performed at the same time in order to play well. This is called as “multiple game interactions overload (Ang et al. 2007).” In addition, they have to interact with both the game and other players. For example, a player has to talk to other players, which is social interaction and to kill monsters, which is game interaction at the same time when the player performs a mission or a quest. This is called as “parallel game and social interactions overload (Ang et al. 2007).”

### ***Virtual team***

An organization's ability to create and share knowledge is important for establishing and sustaining competitive advantage in rapidly changing business environment (Teece et al. 1997). And teams in organizations play a key role to create and share knowledge. Thus, it is crucial that organizations identify and leverage team members' knowledge (Kanawattanachai and Yoo 2007). Teams are the key building blocks of knowledge-based organization (Leonard and Sensiper 1998) and become more and more virtual, in that they are often geographically dispersed and communicate via CMC tools (Jarvenpaa and Leidner 1999). In online games, a virtual team is a workgroup operating in virtual world. It is formed by individual players accessing the same virtual environment from different physical locations (Manninen 2001). The distributed team is one which is geographically dispersed to a greater or lesser extent, such that the team cannot have direct face to face contact with each other for significant parts of its operational activities (Pascual et al. 1999). In general, organizations rely heavily on virtual teams for key operations, such as product development, strategic analysis, and customer service (Majchrzak et al 2000; Maznevski and Chudoba 2000). However, such teams pose a particular challenge for knowledge coordination, as knowledge is distributed across team members (Cannonbower et al. 1993; Faraj and Sproull 2000). A problem distributed members have encountered is the difficulty of getting members to participate and then maintain engagement over time (Nunamaker 1997). Team based incentives and rewards stimulate peer pressure form with the group. Cooperative incentive structures reward individual group members based on the performance of the group. These structures can lead to cooperative behavior among team members. This is particularly interesting within team games that require the contributions of each member in order to accomplish the task assigned to their team (Manninen 2001).

### ***Information flow via social networks***

Sharing information or know-how can improve an individual player's handling of recurrent search problems (Szulanski 2006). Within work teams, individuals who have numerous positive social connections gain access to information and assistance that others lack (Katherine et al. 2004). An individual with diverse social network derives information benefits because he can access more accurate information via the social networks (Burt 1972). Furthermore, the centrality within the social networks yields substantial benefits, including influence, access to information, positive performance ratings (Baldwin et al. 1997; Ibarra & Andrews, 1993).



In our study, party<sup>4</sup> members seek and access information socially through language-based communication. The structure of social information acquisition is instantiated in communication networks that connect other party members with online game servers and text-based chat channels. However, the chat channel might be crowded with non-textual data, such as players taunting each other, complaining about the network delays, or just exchanging experience with others. Thus, the contextual messaging is mostly used to provide information (Manninen, 2001).

#### Time productivity (work or leisure)

Using division of labor, a group can produce more than the sum of the outputs that each can produce alone. And work and leisure are often part of a group behavior in the sense that the willingness of each person to exert effort or to consume leisure depends on the choices of others in some reference group (Weiss 2009). Leisure is time intensive and does not indirectly contribute to earnings (Becker 1965). Leisure is a state of being in which activity is performed for its own sake (Grazia 1962). Both of them describe leisure as a factor to contribute to time productivity. However, the productivity of working time has probably advanced more than that of leisure time, if it is only because of familiar reasons associated with the division of labor and economies of scale (Mitchell 1932). Working time and leisure in real world are compared to battle time and rest time in online games.

We have briefly discussed cognitive load, information flow via social network and team productivity in virtual world. We firstly aim at finding the differences in recognizing cognitive load between new gamers and advance gamers and between non-party members and party members. And we examine the information sharing amongst party members and unit time productivity between a single gamer and party member by conducting social networking analysis. We then quantify the difference in behavioral decisions and time efficiency according to the scale of party members (e.g., single gamer, two gamers... five gamers) by conducting panel analysis. In what follows, we develop our research hypotheses. We then describe the research methodology and key results. Lastly, we conclude our study by discussing the implications of our finding for practice.

### Theory development and hypotheses

Our working memory in human brains makes it difficult for us to understand and process information that is presented to us simultaneously because this creates heavy cognitive load upon users (Wilson and Cole 1996). A user's attention could be focused by directing attention to the information that is most important or immediately relevant (Lee and Lehman 1993). There are techniques to reduce cognitive load in different contexts, some of which can be applied to the playing of online games (Ang et al. 2006). These include eliminating redundant information, combining visual and auditory stimulus and only presenting one representation at a time to the players (Feinberg and Murphy 2000). Most players want a game that is easy enough to learn, but not too easy to the extent because it becomes not challenging (Castronova 2002). For example, the gamers may reduce the difficulty level of the puzzle to reduce cognitive load in the game but they need to solve puzzles and act fast to kill monsters rather than just navigate. Playing game involves interacting with a large number of game objects. A virtual team plays an important role to

<sup>4</sup> A temporal virtual team made up to perform a mission or a quest in online games

reduce cognitive load in the game without reducing the difficulty level of the puzzle (Ang et al. 2006). A virtual team is defined as a temporary, geographically dispersed, and electronically communicating work group. The collaboration among virtual team members is enabled by CMC tools (Jarvenpaa and Leider 1999). Taken together, we hypothesize

- H1: New gamer will reduce the game cognitive load by joining a virtual team, and the reduced cognitive load will positively influence the virtual team performance. However, the cognitive load does not heavily persist throughout the game playing. Thus, the effect of reduced cognitive load by joining a virtual team for advanced gamers will not be as much as that of new gamers.

A virtual environment is computer-generated simulated space with which an individual interacts (Witmer et al. 1996). The networked virtual environment is a software system in which multiple users interact with each other in real time even though they may be located around the world (Singhal and Zyda 1999). Virtual world such as computer games convey information about real world spaces effectively because they tend to preserve the spatiotemporal aspects and natural modes of interaction characteristics of real worlds environments. Virtual team interactions follow the routes of computer mediated communication because it provides means and context for interaction (Manninen, 2001). In social network, the economic value of information stems from its uneven distribution across actors. Individuals solve problems and find opportunities by tapping distinct information pools in diverse network neighborhoods to which their structurally diverse channels provide access (Aral et al. 2011). Social network researchers use a variety of constructs and measures to describe an individual's centrality within a network (Wasserman & Faust 1994). In-degree centrality captures the extent to which individuals in the network identify the focal actor as one of their contacts in the network (Kilduff & Krackhardt 1994). We examine individuals with high in degree information flow centrality are sought in a network based on their CMC servers and channels related access. The centrality within the social networks yields substantial benefits, including influence, access to information, positive performance ratings (Baldwin et al. 1997). Consistently with similarity-attraction theory, a common approach for indexing the similarity of party members is the degree of linear association between the two. We examine the similarity of party members in a network based on CMC servers and channels related access. However, the effects of similarity might be inconsistent (Harrison et al. 2002). Taken together, we hypothesize

- H2: Virtual teams carrying out information sharing through communication networks are more productive. Individual gamers who have the highest in degree information flow centrality are more productive and other gamers who have the closet similarity to them are also productive. However, the comparative superior productivity might be inconsistent because of the effects in unobserved values.

In studies on decision support systems (DSS), decision makers want to make more effective decision, but are limited in terms of cognitive capabilities (Sprague and Carlson 1982). Decision makers are presumed to be bounded rational. As environments require more cognitive effort to process information fully, decision makers often switch to decision strategies or heuristics that are easier to implement, but these heuristics frequently result in less accurate decisions and biased responses (Johnson et al. 1988). Thus, it is clear that people are willing to forgo some benefits to conserve cognitive effort (Garbarino and Edell 1997). Information sharing amongst decision makers will relieve the cognitive effort. However, when information is passed from gamer to gamer, there are an increasing number of chances for misunderstanding or vagueness (Huber & Daft). Thus, when information is vague, virtual teams should take time to verify its accuracy and relevance, and obtain complementary information to enable effective decision making (Hansen 2002). In time allocation theory, Becker (1965) indicates the importance of combining working time with leisure time on time productivity. The allocation of time may be efficiently established by decision makers performing heavy cognitive effort. And positive cognitive effort will be accomplished through knowledge coordination in a virtual team. Taken together, we hypothesize

- H3a: Making a virtual team up will positively influence the efficient allocation of time (working time and leisure). It will positively influence on time productivity. Single gamer and virtual teams who use rest time effectively are more productivity.
- H3b: The behavioral decision of single gamer or between virtual team members might be inconsistent depending on his or each member' capacity. Work difficulty will be positively influence on forming virtual team size.

## Study method

The game we use for this study is one of popular Massively Multiplayer Online Role Playing Games (MMORPGs) in Korea. It requires gamers to make their accounts and log on to play. It designs them to use their avatars identified by character ID. Most players spend much time to develop their avatar's level referring to the strength of the avatars and complete quests or tasks while at the same time allowing them to communicate with other players. A gamer has the opportunity to create and work in a party in the game. For example, a party can be composed of up to 5 players and if all party members are logged out, the party is automatically dissolved. Party members can communicate with one another thus only allowing party members to be engaged in an online conversation. Player can also trade game items and buy online goods from non-playing character (NPC) as well as other players. We conduct our analysis on secondary observations of large numbers of game participants, instead of on primary observations of game playing of a small number of players. Thus, game playing activities involved of hundreds of online game players were took into account in our analysis.

## Data collection

The raw data for this study are obtained from one of top online game distributors in Korea. Seven different dump files containing game activities information are provided from the firm. We extract available data set by aggregating battle time, rest time and experience points per character ID and user ID by using structured query language (SQL). And we extract data set covering server IDs and channel IDs per each character ID forming 5 member virtual teams. In our study, we examine some networking cases.

<b>Table 1. Example of rectangular data array</b>								
	Server1	Server2	Server3	Server4	Server5	Channel1	Channel2	Channel3
Player1	0.198	0.128	0.227	0.268	0.177	0.888	0.061	0.049383
Player2	0.208	0.125	0.138	0.138	0.388	1	0	0
Player3	0.250	0.134	0.192	0.038	0.384	0.8	0.2	0
Player4	0.270	0.173	0.194	0.083	0.277	0.871	0.128	0
Player5	0.185	0.097	0.176	0.097	0.442	0.638	0.361	0

Table 1 shows 1 mode matrix characterizing percentage access rate to server and channel per each party member (Character ID). Each cell indicates the ratio of the number accessing to each server and each channel to the total number accessing servers and channels in a day.

<b>Table 2. Example of square array of network data</b>					
	Player1	Palyer2	Player3	Player4	Player5
Player1	1.007	1.084	0.913	0.975	0.785
Player2	1.084	1.249	1.051	1.097	0.900
Player3	0.913	1.051	0.947	0.962	0.851
Player4	0.975	1.097	0.962	1.002	0.836
Player5	0.785	0.900	0.851	0.836	0.819

Table 2 shows 2 mode matrix transformed from 1 mode matrix for network analysis. The tasks are guided by the research purpose, information flow through social network analysis, behavioral decision amongst party members and virtual team productivity through panel data analysis.

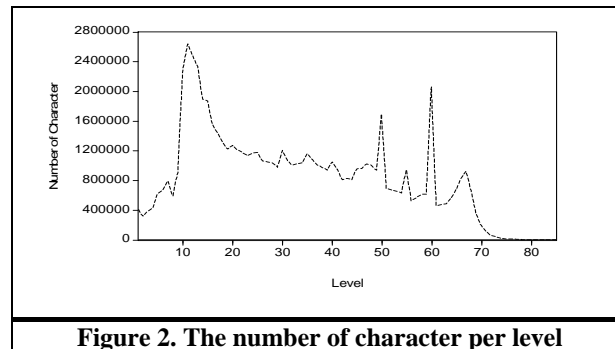


Figure 2 illustrates the number of character ID per each game level from 1 to 75. In the game, game level is designed from 1 to 255, but our manipulated data set does not include the existence of character ID after level 75. We classified the whole group of game players into three different groups depending on their level. For example, new gamers are the player level range from 1 to 20, and middle gamers are from level 21 to 60 and advanced gamers are distinguished after level 60 because the number of character ID is sharply changed at the level 20 and 60.

## Analyses and results

The collected data sets come in various forms. And some econometric methods are applied to three different types of data set (e.g., cross sectional data, time series data and panel data set). We conduct our analyses in two different ways. We use a cross-sectional data set for social network analysis at a specific day. And we use time series and panel data set in the period from May 25 to June 30 in 2010. We conduct our statistical analyses in two steps.

First, we conduct statistical tests to justify the appropriateness of the explanatory variables for econometrical analysis. In order to guarantee the appropriateness of the explanatory variables, we conducted redundant variable test for the explanatory variable rest time to determine whether the variable is significant in determining the logarithm of the experience points. The results give us an F-statistic of 13.276, for comparison to the value of F-critical of 3.84. As F-statistical is greater than F-critical, we can conclude that the coefficient of the variable rest time is not zero, and therefore rest time is not redundant. Second, we test hypotheses by social network analysis and panel data analysis.

### Test of the hypotheses 1

We use ordinary least square (OLS) and generalized least square (GLS) to test hypotheses based on theory development. The built-up model considered on which variables to include or not include making decisions in a cross-sectional data set, and does not suffer from serial correlation and heteroskedasticity in order to be valid in a time series data set. Measures are assessed at two different points (i.e., in an attempt to measure the game cognitive load and in another attempt to measure the game cognitive load and behavioral decision of party member and non-party member).

Logarithmic transformation allows the regression coefficients to be interpreted as elasticities because for small changes in any variable, change in logarithm of the variable is approximately same to relative change in the variable itself. The built-up model regresses log experience points on log battle time and log rest time. Since the dependent variable is log experience points, we can interpret the coefficient value on log rest time and log battle time as the percentage change in log experience points for each unit increase in log rest time and log battle time

$$\text{Base Model: } \log(\text{experiencepoints}) = b_1 + b_2 \log(\text{battletime}) + b_3 \log(\text{resttime}) + e$$

<b>Table 3. A summary results of OLS in the term-end time</b>			
New Gamer level( $\leq 20$ ) Difficulty(df)=1			
PartyMember(PM)=0		PartyMember(PM)=5	
Log(BattleTime)	0.531957***	Log(BattleTime)	0.255893***
Log(RestTime)	0.545656***	Log(RestTime)	0.758169***
Middle Gamer level(21~60) Difficulty(df)=1			
PartyMember(PM)=0		PartyMember(PM)=5	
Log(BattleTime)	0.552007***	Log(BattleTime)	0.320969***
Log(RestTime)	0.669933***	Log(RestTime)	0.866456***
Advanced Gamer level( $\geq 61$ ) Difficulty(df)=1			
PartyMember(PM)=0		PartyMember(PM)=5	
Log(BattleTime)	0.464225***	Log(BattleTime)	0.252165***
Log(RestTime)	0.591240***	Log(RestTime/PM=5)	0.810364***
***p < .001, **p < .005, *p < .01			

Table 3 show that the coefficient value on log rest time is greater than that on log battle time on the whole. In particular, the coefficient value on log rest time in a party is relatively greater than that in non-party. It infers that the collaboration among party members influences positively the virtual team performance. Furthermore, the table illustrates that the coefficient value on log rest time and log battle time increases as the level of the gamers increases, but decreases on the level 61 thereafter. It implicates that the collaborative effect among party members is weakened. That is, mutual dependency between party members decreases after the level 60. The results verify the hypotheses H1. Here, we do not show the sophisticated statistical analysis to measure the game cognitive load due to the lack of complicated variables. However, we try to measure the game load by using the time efficiency because it might be used as a reverse proxy of the degree of game cognitive load.

We analyze the behavior and variability of characters (the gamers) by regressing it on lagged variables as explanatory variables. We exploit the information that is available through the gamers themselves because it might well represent the behavioral decision of party member and non-party member.

$$\text{Base ARMA Model: } \log(\text{numberofcharacterid})_t = b_1 \log(\text{numberofcharacterid})_{t-1} + u_t + c_1 u_{t-1}$$

$$\text{Extended Model: } \log(\text{numberofcharacterid})_t = a + \text{time} + b_1 \log(\text{numberofcharacterid})_{t-1} + u_t + c_1 u_{t-1}$$

The model shows that we are using a time-series model. And it presents growth models of specific numerical indicators (the gamers) using the time variable as an independent variable. Logarithmic transformations are carried out to release some problems from the collected data set. Autocorrelation is most likely to occur in a time-series framework. When data are ordered in chronological order, the error in one period may affect the error in the next or other time periods. Thus, we conduct the Breusch-Godfrey LM test for serial correlation of every model. After transforming the models into ARMA<sup>5</sup> best model, we then got the values of the quite high LM statistic and F statistic, suggesting no serial correlation. The set-up time series model regress on log game players on time and log lagged game players with stationary white noise processes. It implicates that the time series behaviors of gamers are largely determined by their own value in the preceding period. So, what will happen in time t is largely dependent on what happened in time t-1, or alternatively what will happen in time t+1 be determined by the behavior of the series in the current time t. And stationary white noise processes indicates that log gamers depend on the value of the immediate error, which is known at time t (Box et al. 1994). We conduct several different ARMA tests to find best model. In general, the highest value of adjusted R-squared and the lowest value of Akaike info criterion (AIC) and Schwarz criterion (SIC) suggest the most appropriate one. At table 4, the chosen models are all best models.

<sup>5</sup> Autoregressive moving average models, sometimes called Box-Jenkins models



**Table 4. Summary results of ARMA best models**

New Gamer level( $\leq 20$ ) Difficulty(df)=1			
PartyMember(PM)=0		PartyMember(PM)=5	
Variable	Coefficient value	Variable	Coefficient value
Constant	8.510026***	Constant	4.227074***
Time	-0.021553*	Time	-0.030632*
AR(1)	-0.356706**	AR(1)	0.375923*
MA(1)	0.997176***		
Middle Gamer level(21~60) Difficulty(df)=1			
PartyMember(PM)=0		PartyMember(PM)=5	
Variable	Coefficient value	Variable	Coefficient value
Constant	7.038401***	Constant	5.135787***
Time	0.066802*	Time	-0.013615**
Time <sup>2</sup>	-0.001675*	AR(1)	0.725158***
MA(1)	0.483667**	MA(1)	-0.996662***
Advanced Gamer level( $\geq 61$ ) Difficulty(df)=1			
PartyMember(PM)=0		PartyMember(PM)=5	
Variable	Coefficient value	Variable	Coefficient value
Constant	5.480239***	Constant	2.812068***
Time	-0.017701***	Time	0.357143***
AR(1)	0.284042***	Time <sup>2</sup>	-0.027727***
		Time <sup>3</sup>	0.000607***
		MA(1)	-0.332488*
		MA(2)	-0.663121***
***p < .001, **p < .005, *p < .01			

We test the hypotheses H1 by examining the changes in coefficient value of log lagged gamers AR<sup>6</sup> (1). The growth of single gamers does not increase and is affected by the immediate past error MA (1) on the whole. But the growth of advanced gamers after level 60 increases and is not affected by the immediate past error. The growth of new party members increases and is negatively influenced by the immediate past error on the whole. But the growth of advanced gamers does not appear after the level 60. It infers that single gamers do not recognize the importance of collaboration on gaming performance and their activities are likely to be affected by game difficulty, interesting issue, substitutive game, etc as the immediate past errors or other gamers' activities. However, single players after level 60 are likely to reflect other players' activities (e.g., AR (1): 0.284042\*\*\*). On the other hand, the party members understand and reflect the party member's activities and other gamers' gaming information. However, the collaboration among party members decreases particularly advanced party players after level 60 (e.g., AR (1): 0.375923\*, AR (1): 0.725158\*\*\*, AR (1): none) which indicates the favor game activities of high level party members. The results verify the hypotheses H1.

### ***Test of the hypotheses 2***

We analyze information sharing within a party (virtual team) to measure information flow centrality amongst party members. We conduct variables for online game servers and text based chat channels. Measures of the level of servers and channels traffic quantify the ratio of the access number of servers and channels to the total access number of servers and channels. The information flow centrality is indexed by in degree and out degree centrality, which measure the frequency weighted number of access. We also measure other information flow index: Bonacich centrality and Bonacich power. Freeman (1979) developed basic measures of the centrality of actors based on their degree with which is out degrees and in degrees of the Knoke information network, and the overall centralization of graphs. However, Bonacich (1987) proposed a modification of the degree centrality approach. The Freeman's

<sup>6</sup> Lagged variable of log game players

centrality argues that actors who have more connections are more powerful. This makes sense, but having the same degree does not guarantee equal importance. Thus, Bonacich (1987) developed a measure that it assigns relative scores to all actors in the network based on the principle that connections to high-scoring actors contribute more to the score of the actors than low-scoring actors. We analyze 9 virtual team cases and compare unit time productivity.

<b>Table 5. Unit time productivity b/w single and party member</b>				
Party Member (Game level)	Time productivity (per time unit) comparison (Case1)			
	Battletime (single)	Battletime (party)	Resttime (single)	Resttime (party)
Player1(level59)	9482.607	9588.069	4721.565	4109.172
Player4(level47)	6258.103	6870.755	1507.899	1363.172
Player1(level47)	5800.934	15722.036	1911.609	1618.445
Player2(level41)	3527.274	6928.396	1331.353	1319.694
Player4(level46)	8671.145	21560.588	3175.460	2755.865
Player1(level37)	2810.419	4217.762	1379.847	477.778
Player4(level36)	3181.455	7541.962	1986.974	524.775
Player5(level39)	1491.800	9652.106	549.318	737.796
Player3(level47)	2986.064	14603.383	1363.238	1733.664
Player1(level24)	707.346	909.685	367.406	254.919
Player3(level25)	1231.065	573.469	697.496	296.889
Player4(level26)	1113.809	1140.600	701.198	450.935
Player5(level25)	543.837	5606.966	212.659	612.613
Player4(level37)	2658.979	5277.516	1211.886	1138.916
Player5(level39)	475.261	3916.427	270.355	741.621
Player5(level65)	28296.775	24510.443	6489.549	6754.298
Player2(level26)	503.652	2125.708	213.707	756.662

Table 5 shows unit time productivity when a gamer plays game alone and plays game as a party member in a day. The result indicates unit battle time productivity of party member is greater than that of single gamer. We then test relationship between time productivity and information flow centrality (e.g., in degree centrality, Bonacich centrality and Bonacich power) using Generalized Least Squares (GLS) at the 9 cases data set. More detail regarding statistical specification is reported in Appendix A.

<b>Table 6. Network centrality and time productivity</b>					
Method	Dependent variable – Log(experiencepoint)				
	GLS: White Heteroskedasticity-Consistent Standard Errors & Covariance				
	Model1	Model2	Model3	Model4	Model5
Constant	2.706073***	3.044710***	2.742971***	2.728510*	1.035975
Game level	0.036785***	0.032503***	0.036493***	0.036382***	
Log(battletime)	-0.093482	0.142585	-0.068458	-0.062554	
Log(restime)	0.844133***	0.603748***	0.807159***	0.798918***	
Indegree centrality	-0.147321**			0.052115	6.234740**
Eigenvector		-1.109887		0.057682	11.02291
Bonacich Power			-0.109566**	-0.149543	-4.914724**
N	17	17	17	17	17
F	51.58929	40.51999	52.20068	29.01008	1.843821
Adjusted-R <sup>2</sup>	0.926726	0.908088	0.927537	0.913072	0.136604
Akaike info	-0.947378	-0.720761	-0.958515	-0.723538	1.481680
Schwarz criterion	-0.702315	-0.475698	-0.713453	-0.380450	1.677730
* $p < 0.1$ , ** $p < 0.05$ , *** $p < 0.01$ ; Bonacich Centrality(Eigenvector)					

We examine GLS estimates of the relationships. The relationship between input variables, information centrality variables and output variables do exhibit some noise. For example, the estimate of log battle time is never significant,

and information sharing is negatively correlated or does not contribute to the time productivity in a traditional production model. However, model 5 shows that in degree centrality and Bonacich Power are significant at 5 % significant level. Freeman's approach (e.g., 6.234740\*\*) in which same degree signifies equal importance and Bonacich's approach (e.g., -4.914724\*\*) in which same degree does not stand for equal importance verify the hypotheses H2 "Individual gamers who have the highest in degree information flow centrality are more productive. However, the comparative productivity might be inconsistent because of the effects of deep similarity in unobserved values."

### Test of the hypotheses 3a

Many time series exhibit a strong trend of a consistent upward or downward movement in the values. When this is caused by some underlying growth process, a plot of the series will reveal an exponential curve, which dominates other features of the series, it obscure the more interesting relationship between this variable and another growing variable (Box et al. 1994). Thus, we took the natural logarithm of our time series data in order to linearize the growth trend.

$$\text{Base Model: } \log(\text{experiencepoints})_t = b_1 + b_2 \log(\text{battletime})_t + b_3 \log(\text{resttime})_t + u_t$$

$$\text{where } u_t = \rho_1 u_{t-1} + \varepsilon_t$$

One factor that can cause serial correlation in error term is omitted variable. For example, the set-up model supposes that log experience points are related to log battle time and log rest time. But if it does not include any important explanatory variable in the model, the effect of the omitted variable will be captured by the disturbance term. And heteroskedasticity is more likely to take place in a cross-sectional framework, but heteroskedasticity can appear in time series models. Thus, we regress log experience points on log battle time, log rest time and AR<sup>7</sup> (1) by applying GLS. And then, we conduct the Breusch-Godfrey LM test for serial correlation and the White test for heteroskedasticity. The results indicate no serial correlation and no heteroskedasticity for every model.

Table 7. Summary results of GLS models with no serial correlations			
New Gamer level(≤20) Difficulty(df)=1			
PartyMember(PM)=0		PartyMember(PM)=5	
Variable	Coefficient value	Variable	Coefficient value
Constant	7.074599***	Constant	4.529101***
Log(BattleTime)	0.727770*	Log(BattleTime)	0.487344**
Log(RestTime)	0.157147	Log(RestTime)	0.600084**
AR(1)	0.738062***		
Middle Game Player level(21~60) Difficulty(df)=1			
PartyMember(PM)=0		PartyMember(PM)=5	
Variable	Coefficient value	Variable	Coefficient value
Constant	8.388073***	C	7.989029***
Log(BattleTime)	-0.359374	Log(BattleTime)	0.581116***
Log(RestTime)	1.260880*	Log(RestTime)	0.434923**
AR(1)	0.836200***		
Advanced Game Player level(≥61) Difficulty(df)=1			
PartyMember(PM)=0		PartyMember(PM)=5	
Variable	Coefficient value	Variable	Coefficient value
C	6.697114***	C	7.528216***
Log(BattleTime)	0.184839**	Log(BattleTime)	0.397207***

<sup>7</sup> Autoregressive disturbance term

Log(RestTime)	0.956863***	Log(RestTime)	0.703159**
***p < .001, **p < .005, *p < .01			

We then test the hypotheses H3 by examining the changes in coefficient value of all variables. We find the high coefficient values of AR (1) on models based on the single players of the level range from 1 to 60 (e.g., AR (1): 0.738062\*\*\*, AR (1): 0.836200\*\*\*). However, any coefficient value of AR (1) from the players after level 60 did not appear on the model. The results indicate that any important factor is omitted in predicting log experience points in the model. It infers that the single gamers do not use efficiently time to make performance. However, they after level 60 overcome the inefficient allocation of time. On the other hand, we cannot find any coefficient value of AR (1) on the virtual team models. It infers that the party members conduct the efficient allocation of time to perform the collaborative game activities and make performance in virtual teams.

We test relationship between log experience points, log battle time, log rest time, log gamers, and interaction of log battle time and log gamers using feasible generalized least squares (FGLS), fixed effects and random effects at the daily level. We use cross-section seemingly unrelated regression (SUR) weighted least squares on panel model specifications where the residuals are both cross-sectionally heteroskedastic and contemporaneous correlated. We then conduct Hausman tests of the efficiency of random effects specifications and most tests reveal the random effects to be efficient.

Table 8-1. Summary results of individual panel data analysis

Dependent variable – log(experiencepoint)									
Gamer level	low difficulty / low level			low difficulty / middle level			low difficulty / High level		
Method	FGLS	FE	RE	FGLS	FE	RE	FGLS	FE	RE
Constant		7.574***	6.157***		7.070***	10.36***		10.33***	8.981***
log(battle)	1.555***	0.297	0.939***	2.027***	0.883***	0.455**	1.594***	0.175	0.162
log(rest)	0.570***	0.267	0.002	0.720***	0.417**	0.358***	0.532***	0.368***	0.617***
log(gamers)	0.894***	-0.159	0.275**	0.718***	0.062	-0.481***	1.950***	-0.018	0.052
log(battle)* log(gamers)	-0.186***	0.039	-0.052	-0.190***	-0.036	0.044*	-0.253***	0.044	0.026
PM0		-0.208663	-7.54E-12		-0.062966	-5.36E-11		0.182078	3.55E-12
PM2		0.029299	2.35E-12		-0.109879	-9.98E-12		-0.035434	-6.36E-12
PM3		0.100751	9.27E-12		0.068369	9.11E-11		-0.177932	-2.11E-12
PM4		0.074607	-1.76E-12		-0.032914	-2.31E-10		-0.031064	1.53E-12
PM5		0.004006	-2.32E-12		0.137390	2.04E-10		0.062352	3.38E-12
N	170	170	170	170	170	170	160	160	160
F		81.48354	142.3658		310.3747	568.8865		515.5524	890.5711
Adj-R <sup>2</sup>	0.716660	0.792094	0.769900	0.881565	0.936082	0.930753	0.878458	0.962811	0.957227

\*p < 0.1, \*\*p < 0.05, \*\*\*p < 0.01; PM(Party Member), FE(Fixed Effect), RE(Random Effect)

Table 8-2. Summary results of individual panel data analysis

Dependent variable – log(experiencepoint)									
Gamer level	high difficulty / low level			high difficulty / middle level			high difficulty / High level		
Method	FGLS	FE	RE	FGLS	FE	RE	FGLS	FE	RE
Constant		5.574***	6.019***		4.804	3.491		7.030***	8.125***
log(battle)	0.931***	0.453***	0.388***	0.992***	0.262	0.519	1.189***	0.447***	0.172
log(rest)	1.151***	0.578***	0.570***	1.508***	1.428***	1.372***	1.029***	0.640***	0.740***
log(gamers)	0.568***	-0.044	-0.036***	0.612***	-0.125	0.150	1.609***	0.495***	0.098
log(battle)* log(gamers)	-0.126***	0.003		-0.157***	-0.031	-0.074	-0.228***	-0.043**	0.018
PM0		-0.068763	-2.11E-15		-0.017637	-3.82E-12		0.108701	0.000000
PM2		-0.021689	-9.10E-15		0.047523	7.93E-12		-0.066812	0.000000
PM3		0.029563	5.47E-15		0.022683	1.29E-12		-0.048566	0.000000
PM4		0.060889	5.75E-15		-0.019025	-5.95E-12		-0.005733	0.000000
PM5					-0.033544	5.47E-13		0.012410	0.000000
N	136	136	136	170	170	170	160	160	160
F		281.8586	647.0655		43.14958	86.08894		462.9977	802.1734
Adj-R <sup>2</sup>	0.893135	0.935745	0.934883	0.665201	0.666138	0.668208	0.922361	0.958755	0.952731

\*p < 0.1, \*\*p < 0.05, \*\*\*p < 0.01; PM(Party Member), FE(Fixed Effect), RE(Random Effect)

Table 8 shows that most coefficient values of FGLS are overestimated compared to those of FE and RE because unobserved omitted variables are not considered. A central result is that the key driver of time productivity is the log rest time (e.g., RE: 0.358\*\*\*, FE: 0.368\*\*\*, RE: 0.570\*\*\*, RE: 1.372\*\*\*, RE: 0.740\*\*\*). It verifies that as single gamer or virtual teams use leisure more effectively, time productivity increases.

### Test of the hypotheses 3b

We estimate the base model using a fixed effects specification on daily panels. We employ fixed effects to examine individual specific effects of virtual team size or team network size (e.g., 2 ~ 5 gamers).

<b>Table 9. Fixed individual specific effect of virtual team size</b>						
Dependent variable – log(experiencepoint)						
Method	Fixed effect estimate					
Game difficulty	Low difficulty			High difficulty		
Model	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gamer level	Low	Middle	High	Low	Middle	High
Constant	7.400118***	-0.705964	8.334618***	4.924883**	-28.44641***	4.681912
Log(battle)	0.213135	0.212241	0.368877	0.591063**	-2.277936**	-0.201375
Log(rest)	0.263400	2.384114***	0.673003	0.546051	8.439027***	1.731861**
Log(gamers)	-0.292761	1.700088***	0.278644	-0.054991	5.354982***	1.056741*
Log(battle)* Log(gamers)	0.051632	0.071166	0.019589	-0.009609	0.353289**	0.132894*
Log(rest)* Log(gamers)	0.022933	-0.340029***	-0.052531	0.004076	-1.187538***	-0.268732*
Log(battle(-1))	-0.065453	0.128744	-0.032043	-0.223050**	-0.532609**	-0.089336*
Log(rest(-1))	0.102164	-0.253586**	-0.081915	0.215870*	0.929701***	-0.003640
Log(gamers(-1))	-0.012560	-0.075495*	0.114326***	0.049618**	-0.108518	0.072620***
Log(gamers)* week	-0.014793**	-0.001666	-0.002194	0.004212	0.014755**	-0.004244
PM0-constant	-0.404913	0.251462	0.196143	-0.025499	0.418653	0.188030
PM2-constant	-0.015470	-0.056410	-0.056358	-0.020913	0.220832	-0.031348
PM3-constant	0.098882	-0.089032	-0.063819	0.013906	0.017147	-0.042887
PM4-constant	0.174738	-0.132806	-0.083438	0.032506	-0.192981	-0.054266
PM5-constant	0.146762	0.026786	0.007472		-0.463652	-0.059529
N	165	165	155	132	165	155
F	48.58701	220.4803	443.4201	180.5967	35.84506	369.7387
Adjusted-R <sup>2</sup>	0.790450	0.945646	.973922	0.942699	0.734192	0.968874
*p < 0.1, **p < 0.05, ***p < 0.01						

All models specify that the intercept parameters vary only across different size virtual team (e.g., single player and 2 ~ 5 player team). That is, all behavioral difference between individual virtual team are captured by the intercept (e.g., PM0~PM5). Table 9 shows that the individual specific coefficient value of PM4 is highest in model 1 and 4 while the coefficient value of PM0 is highest in model 2, 3, 5 and 6. The individual specific effect of single gamer is lowest in model 1 and 4 while the effect of 4 or 5 team sizes is lowest in model 2, 3, 5 and 6. The highest coefficient value signifies that there exist unobserved omitted factors to contribute to time productivity, while the lowest value signify that existing independent variables contribute to time productivity well. Thus, the results imply that virtual team composing new gamers might not use time efficiently as much as virtual team composing middle and advanced gamers. In another view, new single player try to use time to make performance while middle and advance single gamer use other factor to make better performance (e.g., full information). Furthermore, as game difficulty increase, virtual team size positively affects the time productivity.

## Limitations

Despite contributions to the literature, our study has some limitations that the reader should consider in evaluating the results. Most important, our study is conducted on secondary observations of large numbers of game participants, instead of on primary observations of game playing of a small number of players. Although our analysis on secondary data set provide reasonable results, the experiment adopted an in-depth data collection requiring experimental gamers to play the game for many hours is likely to provide more sophisticated and dynamic results that can be matched to the hypotheses we set up. Thus, in future study, it will be effective to run the experiment with sufficient gamers to overcome the individual difference in the game.

In general, endogeneity can arise as a result of measurement error, autoregression with autocorrelated errors, omitted variables, sample selection errors, and the reverse causality between the independent and dependent variables in our set-up models. Firstly, we conduct GLS regression of log experience points on log battle time and log rest time. It may cause problematic multicollinearity due to inter-correlations among the explanatory variables of log battle time and log rest time. Although we verify the significance of log rest time on the regression by carrying out redundant variable test, if the value of the correlation coefficient in two explanatory variables is very large, it might be problematic. Secondly, we estimate social networking model using GLS on virtual team sampling composing character IDs because we could not extract user IDs format team sampling. Thus, if we sample virtual teams comprising two user IDs each managing 3 characters and 2 characters, the sample based estimation can leads to endogeneity. Lastly, we test hypotheses 3 using FGLS, a fixed effects and a random effects specification on daily panels of time and gamers variables. We then examine user IDs based individual specific effects of different virtual team size (e.g., single, 2 ~ 5 gamers). The problem is that individual gamers play the game alone or join in different size teams in a day. It can lead to endogenous individual specific effects because of an identical gamer forming different size team.

Other shortcoming is related to the measure of cognitive load and virtual team performance. In our study, the cognitive load is measured based on time efficiency estimation. And the performance is based on an objective measure provided by obtained experience points in the game. The measure used in the game represents only one dimension of virtual team effectiveness. Thus, other measure to quantify cognitive load and team performance should be considered in future study.

## Implications for Practice

Online gamers have option to join a virtual team or not to join. Meanwhile, however, in professional environment as the majority of projects in consulting, joining a team is compulsory because such works cannot be completed by a single person. Despite of the fact, our results provide important managerial implications for online game firms or organizations that are using virtual teams for critical tasks. We suggest that game designers can help new gamers cope with cognitive load. The game will remain challenging fun by handling cognitive load better. It will become more manageable for new gamers at the same time.

In organization, manager should focus on supporting the coordination of specialized knowledge of team members in the realm of the task requirements. Information sharing between team members can play a key role to make better performance. Objective measure of information flow through social networks, specifically information flow centrality in virtual team, can provide a sophisticate management to finish project level task successfully. For example, the economic value of information stems from its uneven distribution across virtual team members. Thus, team manager should understand information centrality, similarity and information flow between members and should provide reasonable rewards to team members depending on each one's contribution to information sharing and productivity.

Time management of work and leisure can be an important factor for team collaboration. And flexible formation of virtual team size based on work intensity can contribute to better performance. For example, sophisticated and dynamic systems that reflect information worker's time allocation and on-going single or team centered missions could be even more effective.

## Conclusion

Studies on virtual team performance in organizations have become more common. However, studies on virtual team performance in virtual world have few conducted. Information workers in different levels gain access to information through diverse social networks and information technology in order to diminish overall workloads. Online gamers also try to gain access to information through virtual social network and CMC tools in order to gain more rewards or virtual life's satisfaction from cyber social interaction with someone. Information flow and business or personal value of IT coexists in real and virtual world. Thus, our study examines information, information technology and its value to understand how the information via social network affects productivity in real or virtual world.

Our first contribution to the research literature is that we explore the team performance of information technology (IT) in virtual world. The virtual world not only continues to grow, but also its significance over the entire economy cannot be underestimated even now. IT plays a key role in improving and innovating virtual team collaboration or information sharing process. Thus, it is imperative for managers of the virtual worlds to understand the impact of IT investment on the efficiency of those. However, few quantitative and empirical studies have been conducted on virtual world and virtual team. As far as we know, no comprehensive studies on virtual world have been done based on secondary observations of large numbers of game participants because past studies have been conducted based on primary observations of game playing of a small number of players even though each study has the merits and demerits for the study of virtual worlds. Thus, we believe that our study develops literature on the virtual world and offers important evidences that IT can create business or personal value in virtual worlds. Our second contribution is that we apply social network analysis to our online servers and channels data and found the importance of information centrality to virtual team performance. In a small team network in which information sharing is conducted in the mutual direction, information centrality of Freeman's approach positively contribute to productivity, but Bonacich's approach does not show the positive contribution to productivity. Finally, we validate the importance of leisure and the team size in work intensity. We estimate the individual specific random effect for time efficiency and the individual specific fixed effect for virtual team size efficiency using daily panel data set. The results show that the leisure plays a key driver to make better productivity and virtual team size should increase for the intensive work in order to make better performance. Consequently, we find that the team based collaboration through information sharing can positively contribute to better performance at least in a team network scale. And it clearly validates the team performance value of IT investment in virtual worlds. Now we want to explore whether the efficiency of online service achieved by IT investment leads to higher quality of service in whole virtual world network. And we want to quantify the proposition for the better management of virtual economy.

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