

The acquisition of skill and expertise in massively multiplayer online games

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Abstract Educational learning environments have changed dramatically in the last 20 years. Advances in technology have enabled the World Wide Web and a sundry of other tools. In response, many researchers have argued that one way to understand learning in a complex world is to examine user interactions within Massively Multiplayer Online Games (MMOGs) [Gee (2003). *What video games have to teach us about learning and literacy*. New York: Palgrave/St. Martin's; Squire (2003). *Educational Researcher*, 35(8), 19–29; Young, Schrader, & Zheng, 2006]. However, few empirical investigations have explored MMOGs as a context for learning. As a result, a 20-item, Likert-type instrument was administered to 2140 participants who actively play MMOGs. Items were designed to measure players' gaming experiences as they developed requisite skill sets and learned game content. Specifically, this investigation examined how participants' age ranges and levels of expertise relate to behaviors, strategies, and skills exhibited with an MMOG environment. Although results are not necessarily conclusive, implications for understanding gaming expertise in contemporary educational environments are discussed.

Keywords Expertise · Massively multiplayer online games · Age · Technology · Education

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Introduction

There is little dispute that videogames have become a permanent fixture in global culture. Massively Multiplayer Online Games (MMOGs) have become both a national and international phenomenon, spawning additional game-for-pay industries in Asia (Bailey 2006). These types of games are both fun and popular, facts that are rarely in doubt. The tremendous annual revenue and growing popularity is often cited to support these claims. After all, the World of Warcraft (or WOW, a highly popular and publicized MMOG) has seven million subscribers worldwide, contributing to its fair share of a seven billion dollar industry (Entertainment Software Association 2006; Harper 2006). This widespread popularity has caused considerable interest not only in the commercial sector, but also for educators and academic researchers.

It is commonly agreed upon that games are pervasive. Yet, there is some dispute over their contribution in terms of understanding cognition and to education as a potential context for learning. This dispute is illustrated by academic interest in negative aspects of games as well as helpful, positive outcomes of playing (Schrader 2004). For example, researchers have examined negative videogame characteristics and consequences including gender bias, addiction, and aggression (Anderson and Bushman 2001; Gentile et al. 2004; Kafai 1996; Salguero and Moran 2002; Sherry 2001; Webber et al. 2006). Similarly, researchers have also investigated a wide array of helpful outcomes, including positive influence on motivation and reinforcement (Malouf 1987; Millar and Navarick 1984), spatial ability (Greenfield et al. 1994; Subrahmanyam and Greenfield 1994), and development of complex motor skills (Day et al. 2001; Mane et al. 1989). Researchers have even explored videogames as a benefit to psychological disorders such as Attention Deficit-Hyperactivity Disorder and Eye Poking behavior in children with disabilities (Shaw et al. 2006; Kennedy and Souza 1995; Lawrence et al. 2002).

However, each study examines noncognitive characteristics of gaming and consequences of game play. There are relatively few studies that examine the relationship between gaming and associated cognitive variables. Even when studies address this connection, they are typically focused on a specific variable, independent of other factors. Further, these investigations typically fall into one of two major categories, cognitive skill improvement (increases in math or reading skill) or cognitive consequences of gaming (increases in achievement) (Din and Calao 2001; Grabe and Dosmann 1988; Krauss 1981). These findings are useful on some levels but treat videogames as a tool to deliver information. This perspective is not in line with contemporary views of videogames as interactive, dynamic environments and not simply delivery mechanisms (Young, Schrader, & Zheng, 2006). More specifically, studies of this ilk have not adopted the view that videogames are an environment “*in*” which (rather than “*from*” which or “*with*” which) valuable learning takes place (Barab et al. 2005; Schrader in press; Young et al. 2006).

Although these distinctions may seem unnecessary or artificial at first glance, they represent corresponding shifts in ideology that also have important implications for researchers. For example, the term learning *from* videogames implies that technology is merely a delivery mechanism (Jonassen 2000; Schrader in press). From this view, researchers typically examine outcome variables as a result of using a tool (e.g., Civilization; Squire 2006). Similarly, learning *with* technology reflects a view in which a human agent works in dynamic partnership with technology (Jonassen 2006; Solomon et al. 1991). Although this perspective is considerably more dynamic and complex, researchers often examine learning as an outcome rooted in a physical environment.

However, MMOGs have no physical counterpart; they are strictly virtual environments. MMOGs are also persistent rather than instanced; users may be able to start and stop other games or learning environments, but MMOGs have a running virtual clock that continues regardless of who is playing. MMOGs are dynamic rather than static; users' influence on the system changes the system. MMOGs are engaging and immersive rather than prescribed; users are thrust into a virtual world they find interesting and enjoy navigating. MMOGs are also highly social and community-based rather than individualistic; users interact with thousands upon thousands of like-minded, goal driven individuals. As a consequence of the community surrounding MMOGs, users also locate, evaluate, and apply information from hundreds of texts and hypertexts related to the game. Based on these attributes, researchers argue that we should examine variables linked to learning as a process following interactions with community members and the system itself (Squire 2006; Young 2004; Young et al. 2006). These variables and behaviors include those associated with intrapersonal collaboration (Steinkuehler 2005), authentic perception-action dynamics (Young et al. 2006), literacy and critical evaluation of information (Gee 2003), and development of competence and skill (Schrader and McCreery 2006).

Although these skills are applied in a context designed for entertainment, Lave and Wenger (1991) have argued that valuable learning opportunities are not necessarily limited to formal education. MMOGs have become so popular that they represent authentic communities of practice and large-scale social systems (Lave and Wenger 1991; Thomas and Brown 2007). The fact that most MMOGs have been designed to amuse is only incidental when one considers the salient characteristics of the game environment and the greater context surrounding it (Steinkuehler 2006). Players study, evaluate, and apply game-related information from multiple sources, talk to one another, and collaborate in order to solve problems they find meaningful. Whether or not players' intentions are perceived to be meaningful to others, it is clear that MMOGs are highly complex goal-oriented environments. Further, MMOGs affords a variety of methods to meaningfully and purposefully interact with the environment and/or other users. Although there are differences between environments built to entertain and those designed for education (e.g., emphasis on learning outcomes, objectives, etc.), learning and interaction within MMOGs bear valuable implications for current and future educational contexts because of these salient features (i.e., system dynamics and affordances).

These salient features also mean that MMOGs are inherently complex. A significant degree of skill, understanding of the game, and game related knowledge is required to perform well. Skills associated with communication, evaluation of information, research, problem solving, and literacy, all become important relative to learning the game. However, while educators know a great deal about each of these skills in traditional environments, little is known about their development within technological environments like MMOGs. As a result, this research uses a MMOG context to examine choices, strategies, and behaviors associated with developing expertise in a highly interactive, social, and dynamic environment.

Theoretical framework

Researchers have investigated the nature of expertise from many perspectives in an effort to demystify the stratification of performance in complex fields (see Bereiter and Scardamalia 1993; Glaser et al. 1988). Without such inquiry, it would be impossible to explain why some individuals rise to excellence and become relative authorities within a

domain or field, while others struggle and fail to achieve more than a modicum of success. According to Glaser et al. (1988), there are seven major attributes that differentiate an expert from a novice. From their perspective, experts (1) excel mainly in their own domain, (2) perceive large meaningful patterns in the domain, (3) solve problems quickly, (4) have superior short and long term memory within the domain, (5) think on a deep semantic level, (6) spend time analyzing problems, and (7) exhibit strong self-monitoring skills. Alexander et al. (2004) summarized literature on expertise and suggested that experts possessed extensive and integrated domain knowledge, determine underlying problem structures, select appropriate solutions, and can access related knowledge with little cognitive effort.

Expertise has been investigated from a number of fields and domains. These include both academic fields (e.g., physics and mathematics) and non-academic field (e.g., chess, typing, and restaurant ordering) (Alexander et al. 2004). However conceived, models of expertise describe characteristics of experts in individual terms. Learner characteristics including automaticity, speed of processing, visualization, etc. have all been used to explain how experts function within their particular domain. Further, attributes like age have been offered to suggest how experts advance within a domain. Specifically, early commitment to a domain corresponds to higher levels of expertise in that domain (Ericsson and Charness 1994). Literature on expertise however, is not necessarily formulated to describe the development of skill in highly dynamic, immersive environments. For example, contemporary digital environments are also highly collaborative and social (Barab et al. 2005). With the exception of the teacher/mentor role in deliberate practice, the literature on expertise rarely addresses social aspects of learning (Ericsson et al. 1993, Ericsson and Charness 1994).

Yet situations arise within MMOGs in that they do not fit a traditional model of teaching or mentorship found within expertise literature. As indicated, these contexts are highly dynamic and social (Barab et al. 2005; Squire 2006). Information linked to performance and knowledge is shared among community members. As a result, individual teacher/mentor roles might no longer be appropriate within the MMOG context. Instead, a dynamic model where interactions among members of the community increase knowledge collectively and as a result of social interaction, would more precisely describe the manner in which underlying social structures of games influence performance, knowledge, and expertise. While the individual unit of analysis might include a single player or mentor/mentee dyad, in MMOGs, progression toward expertise can also be analyzed on the level of group, guild, server, or gaming community. In this regard, the community at large serves the same mentoring function, but the relationships and mechanisms linked to this process are unknown.

Beyond socialization, there are several characteristics of MMOGs that relate to the study of expertise. One mechanism of game structure is the questing system, a fundamental component to MMOGs. Its function is to offer activities for both individual and group participation that enhance the acquisition of game-related knowledge through functional epistemology (learning through doing) (Squire 2006). Various rewards are typically available after successful completion of a quest, including experience, items, or game related information (plot). Effectively, quests provide self-directed tutorial guidance and feedback regardless if there are one or more players. In *Quest Atlantis*, the quest system is the foundation of performance goals and knowledge acquisition (Barab et al. 2005). From this perspective, one might argue that MMOGs contain activities guised as tools for deliberate practice that are intended to increase technical skills, game performance, and content knowledge. From a more industrial perspective, the virtual world acts as the

training facility, quest information becomes the training material, and Non-Player Characters (NPCs) and other players act as the teacher(s) (Ericsson et al. 1993).

According to Murphy and Alexander (2002), expertise is based largely in the development of domain knowledge. Based on the activities described above, this would be no different in MMOGs where users spend tremendous time honing skills, researching information, and testing what they have learned. As with all hyper-environments, users (i.e., gamers) are responsible for efficiently and effectively finding and evaluating information, apprehending information across multiple modalities simultaneously, and orchestrating dynamic strategies that facilitate learning in these complex environments (Grabinger et al. 1997). However, domain knowledge (i.e., game content, plot, etc.) and the means to acquire it are not the only areas in which gamers need to excel. With respect to videogames, successful gamers must also master the technology. Mastering technology is tied to simple tasks like installing and running the game to more complex tasks associated with optimizing the game experience. Some players install complex interface modifications that record data and organize the influx of information. Gamers even build, upgrade, and/or tune their computer hardware in order to maximize their experience. It follows that developing expertise in an MMOG involves interaction with and proficiency in a number of distinct areas.

Contemporary theorists have argued that MMOGs are valuable contexts, the salient features of which provide a foundation to examine nontraditional learning (Gee 2003; Schrader et al. 2006; Squire 2003; 2006). From a simplified view, these games are persistent 3-D worlds in which players are afforded the chance to collaborate, problem solve, and work toward common, self-defined goals. Environmental constraints in combination with player abilities and intentions create a foundation for purposeful interaction. Socially mediated experiences typify the genre, requiring extraordinary levels of collaboration and distributed knowledge as a means to master both game content and mechanics. Further, younger players often have greater access to technology and more time to engage in the game context (Yee 2006). Because of these differences between MMOGs and other domains of learning, the following study examined the subsequent research questions:

- (1) What is the relationship among age ranges and levels of expertise?
- (2) What is the relationship among levels of expertise and game related behavior (e.g., research, communication, problem-solving, etc.)?

Methods and procedures

The study was conducted within the context of an immersive videogame environment, World of Warcraft (WOW). The environment was selected for three main reasons; (1) widespread appeal, (2) provides players with multiple methods of participation, and (3) numerous opportunities for socially mediated or collaborative activities. Additionally, we have noted that MMOGs represent rich contexts for nontraditional learning. Within MMOGs, thousands of gamers may collaborate to address goals defined by themselves or their guild (i.e., group of players). Although the context is not an environment constructed around learning objectives, players apply many higher order thinking skills (e.g., evaluation of information, trial and error processing, etc.) and problem solving strategies (e.g., collaboration, planning, etc.) to succeed. Because this research context is based in WOW, advancement and expertise is operationally defined in terms of game mechanics and user

intent. Specifically, a player who has reached the maximum allowable level, has acquired the maximum level of items permissible, and completed the majority of end game content.

Participants

For this inquiry, data were collected from 2,140 individuals who regularly play Massively Multiplayer Online Games during the fall of 2006. Participants were recruited from game forums and were asked to complete an online questionnaire. The sample included 1817 males (84.9%), 309 females (14.4%), and 14 participants (0.7%) who did not report a gender. Using ranges (i.e., 18–20, 21–25, 26–30, 31–35, 36–40, and over 40), participants indicated that their ages ranged from 18 to over 40 with the largest percentage being between 18 and 25 years of age (65.3%). These data reflected nearly identical trends when compared to existing data from more than 30,000 MMOG players (Yee 2006).

A five point Likert-type inventory (1 = Noobie (a game term for someone who has less play experience than a novice), 2 = Novice, 3 = Proficient, 4 = Expert, and 5 = Master) with an N/A option was used as a measure of game expertise. Participants' average expertise was 4.01 and most players rated their level of expertise with their current avatar Expert or Master (74.0%). The majority of participants reported that they had reached the maximum attainable level for their character (85.0%).

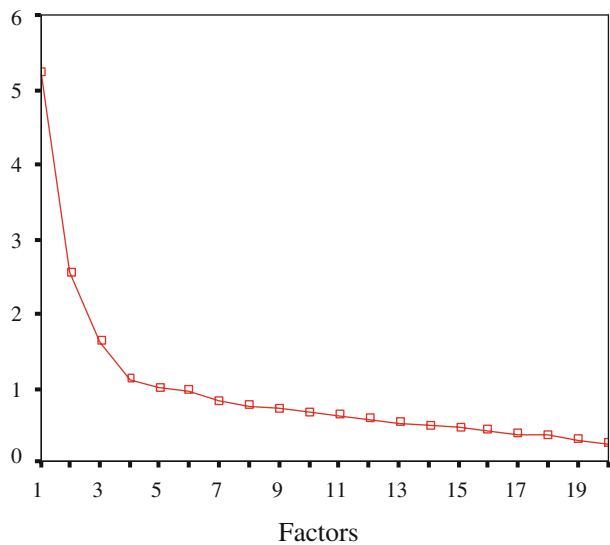
Instrumentation

The instrument for this study was a 20-item, seven point Likert-type inventory (1 = not at all to 7 = very) designed to measure gamers' experiences. The measure had an alpha reliability estimate of .83. The items were informed by research describing expertise as well as literature on games (Alexander et al. 2004; Bransford et al. 2000; Glaser et al. 1988; Schrader and McCreery 2006). Specifically, based on overall characteristics of experts (i.e., extensive domain knowledge, awareness of problem structures, appropriate solutions, and speed of processing), items were reformulated in ways that related to MMOG play (Alexander et al. 2004). Remaining items were intended to measure aspects intrinsic to the MMOG environment such as use of multiple research resources, intertextuality, and social collaboration (see Appendix A for a list of items).

Results

Preliminary data analysis

Based on the fact that the nature and makeup of the factors was unknown in this data set and a large number of dependent variables can obscure meaningful differences in analyses, principal components factoring with a Varimax rotation for interpretation rotation was applied to the data (see Stevens 1996). This was done to (a) reduce the number of variables by (b) detecting the structure and relationships among variables (i.e., classify the variables). The analysis revealed five stable factors using an analysis of the scree plot and eigenvalues greater than one (Cattell 1966; Kaiser 1960) (see Fig. 1). Factor scores were calculated and used as dependent variables in analyses (see Grice 2001).

Fig. 1 Factor analysis scree plot

In a principal components analysis, structure is determined by the degree to which variables (e.g., items) can be grouped based on their correlations. Stevens (1996) suggested that values over .300 indicated sufficient loading for a variable to be included in a factor. Following this guideline, the first factor contained seven items loaded from .401 to .743 and pertained to players' knowledge of and performance within the environment. The second factor contained five items that loaded from .541 to .846 and pertained to players' competence with specific technological resources relevant to play. The third factor contained three items, two of which had loadings of .740 and .749. Item 4, "*I learned what I needed to become an expert from my own trial and error experiences*"; loaded negatively (−.520) suggesting this factor pertained to intrapersonal collaboration. The fourth and fifth factors contained 2 items each that loaded higher than .667 and pertained to non-guild collaboration and status related activities respectively. As a result, these factors were labeled: (1) Game Knowledge and Performance, (2) Technology Competence, (3) Collaboration, (4) Non-guild Collaboration, and (5) Status.

The Kaiser–Meyer–Olkin (KMO) statistic was .844 indicating that variables sufficiently predict one another based on the derived structure (i.e., sampling was adequate and analysis is warranted). Bartlett's test of sphericity was also significant ($p < .001$) indicating that there are sufficient correlations among variables to interpret factor structure. The factors accounted for a total of 57.92% of the variance. Table 1 lists factors, items and their loadings, while Table 2 lists means and standard deviations for the research variables.

Research Question One

In order to determine relationships among age ranges and levels of expertise, a One-Way ANOVA was applied to the data with Age range serving as the independent variable and Gaming Expertise serving as the dependent variable. Tests of assumptions were satisfactory. The ANOVA was significant, $F(5, 2124) = 12.059$, $p < .001$ indicating that there was a meaningful difference between at least one of the levels. Post-hoc comparisons revealed differences on several age ranges with respect to expertise. Further examination

Table 1 Rotated principal components factor loadings

	Loading
Factor 1: Game Knowledge and Performance	
e4) I learned what I needed to become an expert from my own trial and error experiences.	.401
e13) Before a new encounter, I discuss the strategy with my guild.	.529
e14) I constantly evaluate my own performance during game-play.	.620
e15) I understand my character's role in relation to other players.	.704
e16) Other players can rely on me to react quickly.	.743
e17) Before a new encounter, I spend time analyzing the situation.	.665
e18) I understand the underlying game mechanics well (i.e., loot, combat, chat, etc.).	.615
e19) I frequently try to think of new ways to react to in-game situations.	.661
e20) I respond effectively to in-game demands.	.719
<i>Variance explained by this factor</i>	19.68 %
Factor 2: Technology Competence	
e8) While playing, I often have other programs running to check information (i.e., web browser, database, videos, etc.).	.846
e9) While playing the game, I frequently switch between the game and other programs.	.807
e10) I access multiple resources to get game information.	.738
e11) I have significantly modified the interface for my game	.541
e12) I use multiple resources to solve in-game problems and challenges.	.663
<i>Variance explained by this factor</i>	15.12 %
Factor 3: Collaboration	
e1) I reached my level of expertise due to another player's guidance.	.740
e3) I became an expert because of my interactions with members of my guild.	.749
e4) I learned what I needed to become an expert from my own trial and error experiences.*	-.520
<i>Variance explained by this factor</i>	8.70 %
Factor 4: Non-guild Collaboration	
e2) I learned the information necessary to become an expert from my fellow gamers who are not in my guild.	.667
e5) Reading online forums helped me become an expert.	.752
<i>Variance explained by this factor</i>	7.30 %
Factor 5: Status	
e6) I value my success in the game.	.809
e7) I feel that others envy my character's abilities, equipment, etc.	.767
<i>Variance explained by this factor</i>	7.12 %
Total Variance explained	57.91 %

* Item interpreted negatively

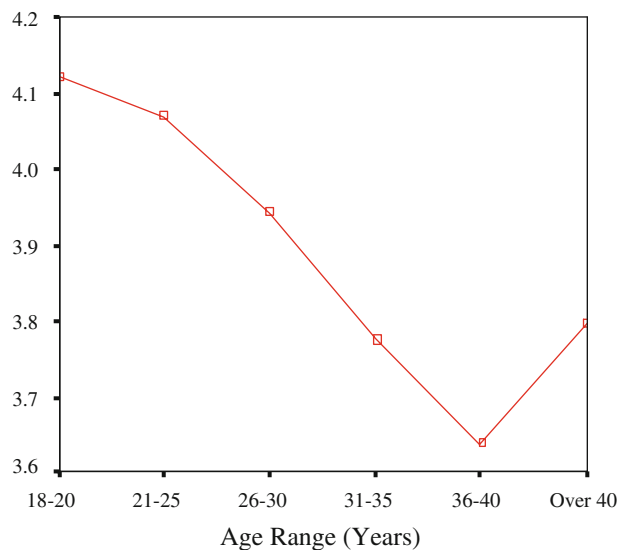
revealed that differences followed a trend and examination of the profile plot suggests that younger players report higher levels of expertise (see Fig. 2).

Research question two

Because the dependent variables (i.e., factors) are interrelated, a Type III sums of squares MANCOVA was applied to the data (Tabachnick and Fidel 1996). This procedure was

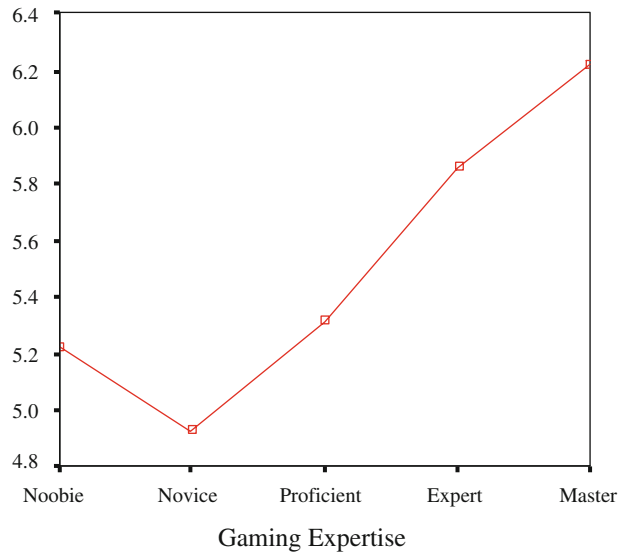
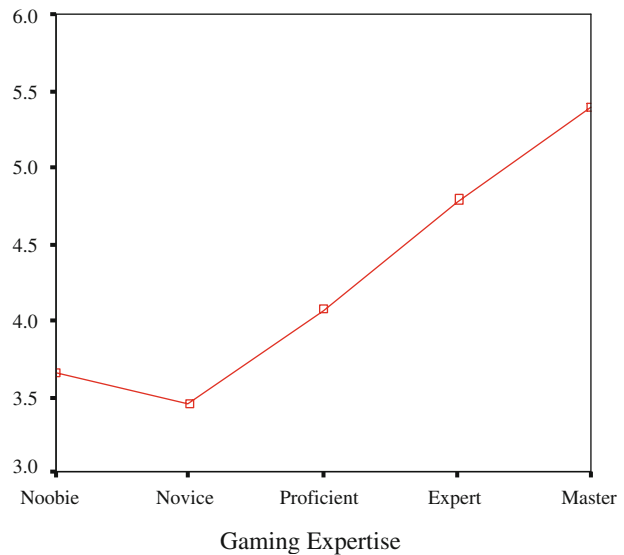
Table 2 Means and standard deviations for the research variables

Variable	N	Mean	Std. Deviation
Age Range	2130	2.30	1.23
Character Expertise	2140	4.01	.79
Knowledge and Performance	2088	5.81	.81
Technology Competence	2087	4.79	1.44
Collaboration	2092	3.36	1.08
Non-guild Collaboration	2088	4.03	1.34
Status	2085	4.77	1.42

Fig. 2 Profile plot for age range and gaming expertise

used to determine relationships among levels of Gaming Expertise and participants' gaming experiences. Following recommendations by Grice (2001), raw factor scores on the original scaling were used in the analysis. In this case, summing responses from the scale and then dividing the total score by the number of items for that factor created the scale score. These five factor variables were entered as dependent variables into the MANCOVA with Gaming Expertise serving as the independent variable. Given the results of research question one, Age range was used as a covariate in this analysis to control for any unintended effects. Results indicate that there was a significant main effect for Gaming Expertise [Wilks' $\Lambda = .735$, $F(20, 2065) = 33.295$, $p < .001$, multivariate $\eta^2 = .074$].

Between subjects analysis revealed that all dependent variables were significant. Gaming Expertise was significant with Knowledge and Performance [$F(4, 2069) = 119.474$, $p < .001$, multivariate $\eta^2 = .188$], Technology Competence [$F(4, 2069) = 18.997$, $p < .001$, multivariate $\eta^2 = .035$], Collaboration [$F(4, 2069) = 15.286$, $p < .001$, multivariate $\eta^2 = .029$], Non-guild Collaboration [$F(4, 2069) = 8.875$, $p < .001$, multivariate $\eta^2 = .017$], and Status [$F(4, 2069) = 80.889$, $p < .001$, multivariate $\eta^2 = .135$]. The estimate of effect for both the Knowledge and Performance and Status

Fig. 3 Profile plot for knowledge and performance**Fig. 4** Profile plot for status

variables are considered large according to Cohen (1988) who characterized $\eta^2 = .01$ as small, $\eta^2 = .06$ as medium, and $\eta^2 = .14$ as large.

Pairwise comparisons for Knowledge and Performance, Technology Competence, and Status revealed a significant general trend supported by the profile plots (see Figs. 3 and 4). For each variable, higher levels of reported expertise coincided with higher scores on Knowledge and Performance, Technology Competence, and Status. However, pairwise comparisons for socialization variables (Collaboration and Non-guild Collaboration) did not reflect a similar trend. With the exception of the lowest level of expertise, the Master level was significantly lower than all other levels, $p < .001$ for the Collaboration variable

Fig. 5 Profile plot for collaboration

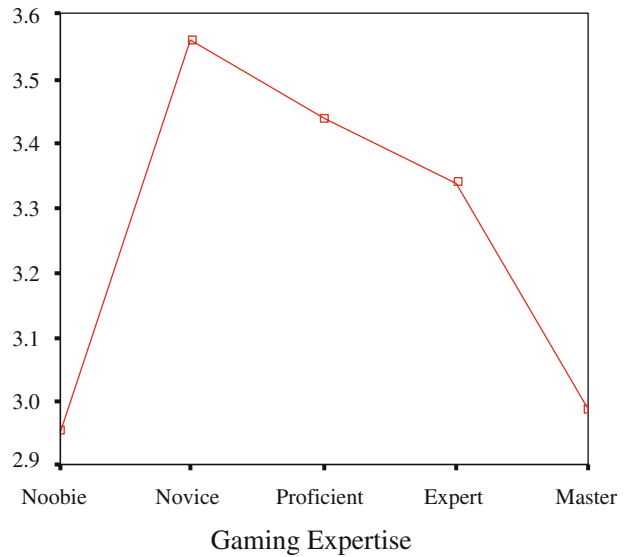
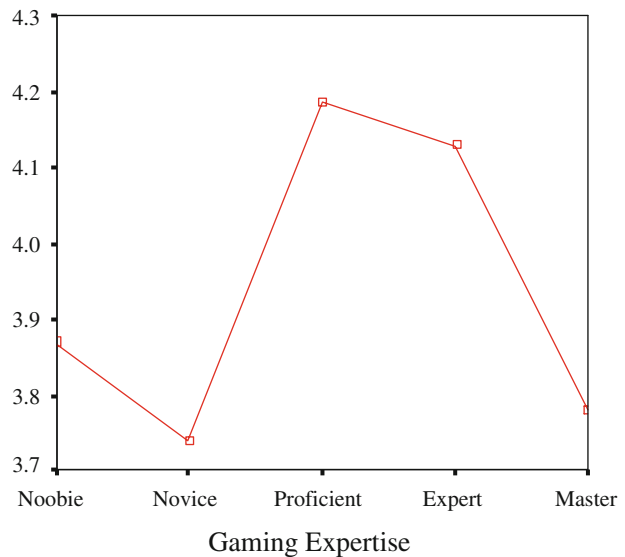


Fig. 6 Profile plot for non-guild collaboration



(see Fig. 5). For Non-guild Collaboration, the Proficient and Expert levels were significantly greater than all other levels, including Master, $p < .001$ (see Fig. 6).

Discussion and implications

Based on a review of the data, several overall trends were evident. The factor analysis revealed five components on which items loaded in interesting ways. Specifically, characteristics of experts described by Glaser et al. (1998) loaded on the Knowledge and

Performance factor such as domain knowledge, speed of processing, decision-making skills, etc. However, researchers have also argued that any hyper-environment is the intersection of at least two domains, the content and the technology (Mitchell et al. 2005). The second factor, Technology Competence, demonstrates that this holds true with respect to this investigation. Beyond the literature on expertise, additional items that pertained to intertextual and intratextual communication, collaboration, and status were clustered together based on the nature of collaboration, rather than the mode of communication. This trend might be due to the highly integrated way in which players in immersive environments utilize multiple tools to communicate with one another. Said another way, for users that negotiate a tremendous wealth of resources with a high degree of competence, to whom they communicate is principal rather than the mode of sending/receiving the information. However, additional research into how gamers locate, evaluate, and apply information from multiple sources and via multiple methods is needed.

Beyond patterns apparent in the data, these findings also reveal some important trends. According to the data, younger participants who engaged in an immersive environment rated their level of expertise significantly higher than older participants. This is not entirely surprising given the technological nature of this context and the opportunity for younger participants to engage with technology in general (i.e., at school, via phones, etc.). Further, Ericcson and Charness (1994) suggested that an early commitment to a domain corresponds to higher levels of potential expertise. Research also suggests that domain knowledge is a principal characteristic of experts (Murphy and Alexander 2002). However, while early adoption and exposure might influence the development of expertise, it is not necessarily clear to what degree experience with technology rather than age influences expertise in this context. For example, additional data regarding overall time engaged in the context, relative speed to achieve goals, and access to technology are a few variables to further explore technology domain expertise.

Although these findings are not conclusive or definitive, they offer some important implications for research in educational settings. For example, it would be valuable to determine what changes might be made to influence the development of expertise and learning in future MMOG contexts designed specifically for education, rather than for purposes of entertainment. Based on the findings in this study, one might speculate that younger students who also have higher technological competence will have a greater opportunity to master the content of future educational MMOGs and other highly complex, immersive environments. Specifically, these learners would demonstrate high levels of technical competence while engaged in the context and be capable of working toward goals and objectives of interactive, multiplayer learning environments with greater ease. As a result of highly defined technological skills, learners are empowered through mechanisms like automaticity and reduced cognitive load.

With respect to expertise, researchers have argued that there are several attributes that distinguish experts from novices (i.e., domain knowledge, speed of processing, problem solving, etc.) (Glaser et al. 1988). These findings support the notion that gamers with high degrees of gaming proficiency engage in specific activities (information gathering and problem-solving prior to activity engagement) unlike less-skilled gamers (activity engagement through trial and error). Expert gamers tend to have higher levels of knowledge and performance than novices or noobies. They report higher levels of awareness and understanding of domain related topics as well as swift and appropriate reaction to domain related challenges. Beyond knowledge, experts have high degrees of specific technological skills that are directly related to the domain. In particular, they utilize multiple resources to locate information, often switching between applications, run multiple applications

simultaneously, and make significant changes to the graphical user interface (GUI). However, it is unknown how players leverage these skills (e.g., technology, multiple source comprehension, etc.) to maximize performance and learning. Additional research is recommended.

While much of the information on experts is consistent with these findings, researchers have also argued that immersive environments such as MMOGs are also highly social (Gee 2003; Steinkuehler 2006). As a result, one might expect higher levels of social interaction among experts as compared to novices. While these findings indicated a general trend that supports this notion, the highest level of expertise demonstrated significantly reduced Collaboration and Non-guild Collaboration scores. Further, the Collaboration (player guidance and guild input) variable demonstrated a decline as the level of mastery increased. By contrast, high levels of Non-guild Collaboration (using forums and other gamers' input) were focused on the midlevel of expertise. Examined collectively, these findings suggest that while collaboration appears to be instrumental at certain cross-sections of expertise, it ceases to be instrumental in achieving objectives at higher levels.

One possible reason for this finding is that regardless of competence, immersive environments like the MMOG are dependent upon collaboration. However, to attain a maximum level of competence, one must be able to move beyond social dependence. Another possible explanation is the presence of a ceiling effect in terms of collaboration. For developing players, social collaboration and mentoring is accentuated. For more proficient and expert players, collaboration may go unrecognized given its fundamental, structural nature.

The findings presented have demonstrated the relationship among expertise and several variables. However, for a few key reasons, it is recommended that these findings be interpreted with caution. A principal concern is that the data in this investigation were self-report. While the use of self-report metrics is often pragmatic, there are known issues with the accuracy and validity of these data. Specifically, it is impossible to determine the extent to which participants behaved as they indicated or their motivation for participating in the study. Future investigations may overcome these limitations by examining gaming behavior in objective ways (e.g., direct observation, log files, or path analysis). Future investigations might also study levels of expertise with less ambiguity by using a social consensus or a set of validated criteria to indicate competence.

In addition to the nature of the data, there are other limitations to this investigation. While levels of expertise and age range were examined, the manner in which one engages in these immersive environments (i.e., play style) was not addressed. Some researchers have argued that play style may account for the adoption of various goals within the system and the manner in which one interacts with others in that environment (Bartle, n.d.; Young et al. 2006). Further, only participants 18 years or older were included in this study. While pragmatic, this sampling neither adequately reflects players who might demonstrate significant variability in their knowledge and skill nor does it generalize to school age students. For example, school age students might have greater access to technology as well as more time available for play. Because both access and time are consistent with increased levels of expertise, additional efforts to collect data from younger participants is advised.

Further, this investigation was conducted within a context designed and intended for entertainment. Although some theorists have argued that studying learning in an environment like WOW provides valuable clues about learning in similar emergent environments, there are arguable differences between environments designed for education and those intended to amuse. For example, the context and structure of information within WOW are neither driven by instructional objectives nor are they focused around learning

outcomes. One might argue that players learn game content as a consequence of an overarching goal, the pursuit of fun, which does not necessarily guide or ensure learning. Additionally, content and mechanics within WOW continually evolve. In an effort to maintain balance, developers modify major aspects of the context (e.g., underlying code, geography, items, etc.) regularly. In major content updates, entire story-arcs can be created, modified, or eliminated in an effort to maintain balance. As a result, the domain of WOW is unstable and learning its content is unlike other domains (e.g., mathematics, literacy, etc.). Although these differences seem obvious, future investigations should examine their influence on the acquisition of knowledge and skill within MMOGs of various designs (e.g., educational vs. entertainment).

While this examination was focused on the description of expertise within a single context, researchers have demonstrated that overall, learning is a multidimensional construct (Murphy and Alexander 2002). Development of skill and expertise depends upon cognitive and non-cognitive factors such as knowledge, interest, and strategy (Alexander et al. 2004). Moreover, research on navigation also suggests that the process of interacting with a hyper-environment is crucial to understanding learning in that environment (Lawless et al. in press). While this investigation revealed additional variables idiosyncratic to the MMOG context (e.g., collaboration and status), future efforts to examine learning in immersive contexts should take these variables into consideration.

Conclusion

Although there are many unanswered questions, we consider these findings to be of significant value. Considering the role of technology in education, each of these outcomes is arguably a highly desirable goal. For example, one would consider it a great success if students actively researched ideas and valued their learning beyond the scope of formalized instruction. In education, one would also consider it a success if students acquired significant levels of domain knowledge. Although WOW is a commercial product intended for entertainment, it is also an ideal context in which cognition and learning may be studied (Steinkuehler 2006). Further, the trends in research and popular culture suggest that understanding learning in such environments is not only timely, but also crucial (Gee 2003; Squire 2006; Young et al., 2006).

While we do not necessarily argue that these findings are generalizable to educational contexts, they may be leveraged in future educational applications. Specifically, dynamic, immersive environments such as WOW provide learners with multiple avenues of support and communication. In modern classrooms, many researchers view learning as inherently social (Choi 2006). The interactive nature of MMOGs provides learners opportunities to access vital information via social networks and construct knowledge as the result of social collaboration. Research also indicates that expertise is related to the acquisition of knowledge and development of performance (Glaser et al. 1988). The structure of MMOGs includes a quest system that promotes deliberate, functional epistemology toward this end (Squire 2006). In a learning context, intentional interaction with knowledge and content is consistent with contemporary constructivist approaches (Jonassen 2006).

While traditional models of expertise do not necessarily emphasize the importance of social collaboration, these findings indicate that socialization has a key influence for some cross sections of the population. Further, social and design structures inherent to MMOGs afford various degrees and types of interactivity, each supporting the development of expertise in unique and interesting ways. While learner variables such as age and

experience appear to be factors, immersive environments of MMOGs provide a structured context intended to promote the necessary skills to accomplish complex, goal-based tasks. Learners are empowered through a dynamic, interconnected process that scaffolds both technological skills sets and content knowledge. These environments provide substantial support and developmental tools for focused goal oriented learning at all levels of expertise.

Appendix A

Items	Not at all somewhat very
1) I reached my level of expertise due to another player's guidance.	1 2 3 4 5 6 7
2) I learned the information necessary to become an expert from my fellow gamers who are not in my guild.	1 2 3 4 5 6 7
3) I became an expert because of my interactions with members of my guild.	1 2 3 4 5 6 7
4) I learned what I needed to become an expert from my own trial and error experiences.	1 2 3 4 5 6 7
5) Reading online forums helped me become an expert.	1 2 3 4 5 6 7
6) I value my success in the game.	1 2 3 4 5 6 7
7) I feel that others envy my character's abilities, equipment, etc.	1 2 3 4 5 6 7
8) While playing, I often have other programs running to check information (i.e., web browser, database, videos, etc.).	1 2 3 4 5 6 7
9) While playing the game, I frequently switch between the game and other programs.	1 2 3 4 5 6 7
10) I access multiple resources to get game information.	1 2 3 4 5 6 7
11) I have significantly modified the interface for my game.	1 2 3 4 5 6 7
12) I use multiple resources to solve in-game problems and challenges.	1 2 3 4 5 6 7
13) Before a new encounter, I discuss the strategy with my guild.	1 2 3 4 5 6 7
14) I constantly evaluate my own performance during game-play.	1 2 3 4 5 6 7
15) I understand my character's role in relation to other players.	1 2 3 4 5 6 7
16) Other players can rely on me to react quickly.	1 2 3 4 5 6 7
17) Before a new encounter, I spend time analyzing the situation.	1 2 3 4 5 6 7
18) I understand the underlying game mechanics well (i.e., loot, combat, chat, etc.).	1 2 3 4 5 6 7
19) I frequently try to think of new ways to react to in-game situations.	1 2 3 4 5 6 7
20) I respond effectively to in-game demands.	1 2 3 4 5 6 7

References

- Alexander, P. A., Sperl, C. T., Buehl, M. M., Fives, H., & Chiu, S. (2004) Modeling domain learning: Profiles from the field of special education. *Journal of Educational Psychology*, 96(3), 545–557.
- Anderson, C. A., & Bushman, B. J. (2001). Effects of violent video games on aggressive behavior, aggressive cognition, aggressive affect, physiological arousal, and prosocial behavior: A meta-analytic review of the scientific literature. *Psychological Science*, 12(5), 353–359.

- Bailey, C. (2006). China's full-time computer gamers. *BBC News*. <http://news.bbc.co.uk/2/hi/business/5151916.stm>.
- Barab, S., Thomas, M., Dodge, T., Carteaux, R., & Tuzun, H. (2005). Making Learning Fun: *Quest Atlantis*, A Game Without Guns. *Educational Technology Research & Development*, 53(1), 86–107.
- Bartle, R. (n.d.). *Hearts, Clubs, Diamonds, Spades: Players Who Suit MUDS*. Online: <http://mud.co.uk/richard/hcds.htm>.
- Berieter, C., & Scardamalia, M. (1993). *Surpassing ourselves: An inquiry into the nature and implications of expertise*. Peru, IL: Open Court Publishing.
- Bransford, J. D., Brown, A. L., & Cocking, R. R., (2000). *How people learn: brain mind experience and school*. Washington, D.C.: National Academic Press.
- Cattell, R. B. (1966). The scree test for the number of factors. *Multivariate Behavioral Research*, 1, 629–637.
- Choi, M. (2006). Communities of practice: An alternative learning model for knowledge creation. *British Journal of Educational Technology*, 37(1), 143–146.
- Day, E. A., Arthur, W., & Gettman, D. (2001). Knowledge structures and the acquisition of complex skill. *Journal of Applied Psychology*, 85(5), 1022–1033.
- Din, F. S., & Calao, J. (2001). The effects of playing educational video games on kindergarten achievement. *Child Study Journal*, 31(2), 95–102.
- Ericsson, K. A., & Charness, N. (1994). Expert performance: Its structure and acquisition. *American Psychologist*, 49(8), 725–747.
- Ericsson, K. A., Krampe, R. T., & Tesch-Romer, C. (1993). The role of deliberate practice in the acquisition of expert performance. *Psychological Review*, 100(3), 363–406.
- Entertainment Software Association (2006). *Essential facts about the computer and video game industry*. Retrieved January 11, 2007, from <http://www.theesa.com/facts/index.php>.
- Gee, J. P. (2003). *What video games have to teach us about learning and literacy*. New York: Palgrave/St. Martin's.
- Gentile, D. A., Lynch, P. J., Linder, J. R., & Walsh, D. A. (2004). The effects of violent video game habits on adolescent hostility, aggressive behaviors, and school performance. *Journal of Adolescence*, 27, 5–22.
- Glaser, R., Chi, M. T. H., & Farr, M. J. (1988). *The nature of expertise*. New Jersey: Erlbaum, Hillsdale.
- Grabe, M., & Dosmann, M. (1988). The potential of adventure games for the development of reading and study skills. *Journal of Computer-Based Instruction*, 15(2), 72–77.
- Grabinger, S. R., Dunlap, J. C., Duffield, J. A. (1997) Rich environments for active learning in action: problem-based learning. *ALT-J. Journal of the Association for Learning Technology*, 5(2), 5–17.
- Greenfield, P. M., Brannon, C., & Lohr, D. (1994). Two-dimensional representation of movement through three-dimensional space: The role of video game expertise. *Journal of Applied Developmental Psychology*, 15, 87–103.
- Grice, J. W. (2001). Computing and evaluating factor scores. *Psychological Methods*, 6, 430–450.
- Harper, E. (2006, September). World of Warcraft hits 7 million subscribers. *Joystiq*. Retrieved January 11, 2007 from <http://www.joystiq.com/2006/09/07/world-of-warcraft-hits-7-million-subscribers/>.
- Jonassen, D. H. (2000). *Computers as mindtools for schools: engaging critical thinking* (2nd ed.). Upper Saddle River, NJ: Merrill.
- Jonassen, D. H. (2006). *Modeling with Technology: Mindtools for Conceptual Change* (3rd ed.). Upper Saddle River, NJ: Pearson.
- Kafai, Y. B. (1996). Electronic play worlds: Gender differences in children's construction of video games. In Y. Kafai & M. Resnick (Eds.), *Constructivism in practice: Designing, thinking, and learning in a digital world* (pp. 97–123). Mahwah, NJ: Erlbaum.
- Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement*, 20, 141–151.
- Kennedy, C. H., & Souza, G. (1995). Functional analysis and treatment of eye poking. *Journal of Applied Behavior Analysis*, 28(1), 27–37.
- Krauss, W. H. (1981). Using a computer game to reinforce skills in addition to basic facts in second grade. *Journal for Research in Mathematics Education*, 12(2), 152–155.
- Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge: Cambridge University Press.
- Lawless, K. A., Schrader, P. G., & Mayall, H. J. (in press). Acquisition of Information Online: Knowledge, Navigational Strategy and Learning Outcomes. *Journal of Literacy Research*.
- Lawrence, V., Houghton, S., Tannock, R., Graham, D., Durkin, K., & Whiting, K. (2002). ADHD outside the laboratory: Boys' executive function performance on tasks in videogame play and on a visit to the zoo. *Journal of Abnormal Child Psychology*, 30(5), 447–462.

- Malouf, D. B. (1987). The effect of instructional computer games on continuing student motivation. *The Journal of Special Education*, 21(4), 27–38.
- Mane, A. M., Adams, J. A., & Donchin, E. (1989). Adaptive and part: Whole training in the acquisition of a complex perceptual-motor skill. *Acta Psychologica*, 71, 179–196.
- Millar, A., & Navarick, D. J. (1984). Self-control and choice in humans: Effects of video game playing as a positive reinforcer. *Learning and Motivation*, 15, 203–218.
- Mitchell, T. J. E., Chen, S. Y., Macredie, R. D. (2005). Hypermedia learning and prior knowledge: Domain expertise vs. system expertise. *Journal of Computer Assisted learning*, 21, 53–64.
- Murphy, P. K., & Alexander, P. A. (2002). What counts? The predictive powers of subject-matter knowledge, strategic processing, and interest in domain-specific performance. *The Journal of Experimental Education*, 70(3), 197–214.
- Salguero, R. A., & Moran, R. M. (2002). Measuring problem video game playing in adolescents. *Addiction*, 97, 1601–1606.
- Schrader, P. G. (2004). Games in education: Beyond arousal, aggression, and gender. *Proceedings of International Conference on Education and Information Systems*, 2004, 207–212.
- Schrader, P. G. (in press). Learning in technology: Reconceptualizing immersive environments. *AACE Journal*.
- Schrader, P. G., & McCreery, M. (2006, June). *How Did You Get so Good? An Investigation of Expertise in the World of Warcraft*. Paper presented at the Games, Learning, and Society Conference, June 15–16, 2006, Madison, WI.
- Schrader, P. G., Zheng, D. P., & Young, M. F. (2006). Teachers' perceptions of video games: MMOGs and the future of preservice teacher education. *Innovate*, 2(3). Retrieved January 11, 2007, from <http://www.innovateonline.info/index.php?view=article&id=125>.
- Shaw, R., Grayson, A., & Lewis, V. (2006). Inhibition, ADHD, and computer games: The inhibitory performance of children with ADHD on computerized tasks and games. *Journal of Attention Disorders*, 8(4), 160–168.
- Sherry, J. (2001). The effects of violent video games on aggression: A meta-analysis. *Human Communication Research*, 27(3), 409–431.
- Solomon, G., Perkins, D. N., & Globerson, T. (1991). Partners in cognition: Extending human intelligence with intelligent technologies. *Educational Researcher*, 20(4), 2–9.
- Squire, K.D. (2003). Video games in education. *International Journal of Intelligent Simulations and Gaming*, 2 (1). Retrieved January 11, 2007, from <http://cms.mit.edu/games/education/pubs/IJIS.doc>.
- Squire, K. D. (2006). From content to context: Videogames as designed experiences. *Educational Researcher*, 35(8), 19–29.
- Steinkuehler, C. A. (2006). Why game (Culture) studies now? *Games and Culture*, 1(1), 97–102.
- Steinkuehler, C. A. (2005). The new third place: Massively multiplayer online gaming in American youth culture. *Tidskrift Journal of Research in Teacher Education*, 3, 17–32.
- Stevens, J. (1996). *Applied multivariate statistics for the social sciences* (3rd ed.). Mahwah, New Jersey: Lawrence Earlbaum Associates.
- Subrahmanyam, K., & Greenfield, P. M. (1994). Effect of video game practice on spatial skills in girls and boys. *Journal of Applied Developmental Psychology*, 15, 13–32.
- Tabachnick, B. G., & Fidell, L. S. (1996). *Using multivariate statistics* (3rd ed.). NY: Harper Collins.
- Thomas, D., & Brown, J. S. (2007). The play of imagination: Extending the literary mind. *Games and Culture*, 2(2), 149–172.
- Webber, R., Ritterfeld, U., & Mathiak, K. (2006). Does playing violent video games induce aggression? Empirical evidence of a functional magnetic resonance imaging study. *Media Psychology*, 8, 39–60.
- Yee, N. (2006). The demographics, motivations and derived experiences of users of massively-multiuser online graphical environments. *PRESENCE: Teleoperators and Virtual Environments*, 15, 309–329.
- Young, M. (2004). An ecological description of video games in education. Proceedings of the International Conference on Education and Information Systems Technologies and Applications (EISTA), Orlando, FL, July 23. <http://web.uconn.edu/myoung/EISTA04Proceed.pdf> (accessed February 10, 2006).
- Young, M. F., Schrader, P. G., & Zheng, D. P. (2006). MMOGs as learning environments: An ecological journey into Quest Atlantis and the Sims Online. *Innovate*, 2(4). <http://www.innovateonline.info/index.php?view=article&id=66> (accessed March 20, 2006).

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