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Heterogeneous knowledge distribution in MMO player behavior: Using domain knowledge to distinguish membership in a community of practice

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ABSTRACT

Current examinations of expertise in the Massively Multiplayer Online (MMO) domain focus primarily on player performance; explorations of player knowledge, however, have the opportunity to meaningfully supplement these studies. Including player knowledge in MMO studies provides the framework needed for a detailed examination of the role of experience and community membership in defining engaged MMO players within a larger population of potential players. Using the Community of Practice framework, we developed a measure of participant's knowledge of MMO specific language to identify individuals who actively engage with other players, a constantly shifting subpopulation who are meaningfully different than those who are not actively participating. We used membership in a community of practice, as determined by our knowledge assessment, to examine the effectiveness of broader demographic questions and more MMO specific demographic questions in creating a predictive model of membership. Our findings indicate that demographics specific to MMO players are more predictive of membership than those used for a general population. Consequently, we recommend that future studies use knowledge-based measures to identify a subpopulation of engaged MMO players within a larger population, allowing researchers to describe their effects with greater precision.

1. Introduction

Research into player behavior within Massively Multiplayer Online (MMO) games approaches the question of player expertise through a performance-oriented framework. While a methodology focusing on player demographics and performance—using efficiency measures, goal directed observation, server-side player statistics, and self-reported player information—is useful for the evaluation of player expertise and relevant game-related behavior, this approach neglects player specific factors that lie outside of game mechanics. In the acquisition of expertise in an MMO, players must deliberately practice skills and achieve a deep and broad knowledge of the MMO (Phillips, Klein, & Sieck, 2004; Schrader & McCreery, 2008). Unlike in single player games, players acquire both skill and knowledge by sharing information with other players and helping them complete joint activities (Ashton, 2009; Carter, Gibbs, & Harrop, 2012). Sharing both experiences and provisional understandings of the game strengthens knowledge of the game for all players. Additionally, these shared experiences establish deep connections among the players engaged (DeSanctis, Fayard, Roach, & Jiang, 2003; Stigliani & Ravasi, 2012; Wenger, 2000); these dialogic negotiations of the MMO, often recorded in online communities created to host these discussions, assist in the formation of a sense of common identity amongst these engaged players (Ashton, 2009; DeSanctis et al., 2003). MMO research that focuses exclusively on the measurement of performance outcomes does not account for the influence of this player interaction and community membership on player behavior. We seek to apply methods and theory established in research on Expertise and Communities of Practice to the MMO domain, using this approach to differentiate users based on their participation in these MMO communities and determine the predictive validity of social learning oriented questions for evaluating a player's skills, compared to the more commonly applied demographic (i.e. player characteristics) and performance based methods.

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1.1. What is an MMO?

The term Massively Multiplayer Online (MMO) game is defined as an online game where users interact in a persistent virtual world, using self-created digital characters known as 'avatars' (Steinkuehler, 2004). These games are complete microcosms, each with their own distinct economy, culture, and social spaces, which can extend outside the game itself (Alemi, 2007; Lin & Sun, 2005; Warner & Raiter, 2005). As players encounter new challenges, they gradually piece together an understanding of the environment and the means by which they can overcome these challenges, in a process known as *sensemaking*. Sensemaking describes the process by which individuals are confronted with an unfamiliar situation and attempt to organize the incoming stimuli into a coherent narrative (Klein, Moon, & Hoffman, 2006; Stigliani & Ravasi, 2012; Weick, Sutcliffe, & Obstfeld, 2005). By repeatedly trying new approaches to gameplay, interpreting ambiguous information received from the game, and reflecting upon the results of individual and collective actions, players create an ever-changing, shared understanding of the world (DeSanctis et al., 2003; Stigliani & Ravasi, 2012).

Players can also acquire information about the MMO playspace through interacting with other players, both within and outside the game. MMOs, by their very nature, are social experiences; players create and maintain social relationships, share strategies, and discuss myriad topics unrelated to the game (Castronova, 2001; Steinkuehler & Williams, 2006; Yee, 2006). MMOs include a feature that allows players to communicate with one another ingame, using either a text-based social interaction system or an integrated voice over internet protocol (Castronova, 2001; Wadley, Gibbs, & Benda, 2007). Through the continuously operating chat interface, players can have the dense dialogue—providing opinions, experimenting with new ideas, and reflecting upon player actions—needed to establish a collective sensemaking process (DeSanctis et al., 2003; Steinkuehler & Williams, 2006; Stigliani & Ravasi, 2012). Players can communicate with one another not only through the game itself, but also through the use of intermediary social spaces (e.g. forums, message boards), to share information within the game community (Ashton, 2009; Castronova, 2001). In these spaces, players can collaborate to explore the limits of the game, and build a coherent, shared understanding of the game and a set of practices based on that understanding (Ashton, 2009; DeSanctis et al., 2003; Kong & Kwok, 2009).

In MMO gameplay, the relationship between the player and the game extends beyond the designer-intended experience; the communal nature of an MMO facilitates communication between players, opening players up to play acts beyond the scope of what the game's designers originally intended (Carter et al., 2012; Steinkuehler & Williams, 2006). Player interaction, both collaborative and competitive, introduces another level of play beyond performing in-game actions in order to achieve game-related goals; consequently, a decomposition of player–player interaction and player–game interaction is pertinent when discussing player behavior in MMOs (Castronova, 2001; see Hoffman, 2013 for a detailed decomposition). We use the term *orthogame*, as established by Carter et al. (2012), to refer to the designer-intended game experience, comprised of in-game activities, challenges, and narratives (Arsenault, 2009; Carter et al., 2012; Taylor, de Castell, Jenson, & Humphrey, 2011). At this level of game experience, players achieve mastery of the game's mechanics, accomplish in-game goals, receive pieces of narrative, and engage with the game environment itself (Reeves, Brown, & Laurier, 2009; Schrader & McCreery, 2008).

We contrast these designer intended experiences with the *metagame*, in which players act or consider resources beyond the scope of the orthogame to accomplish in-game goals or to attain an advantage against other players (Carter et al., 2012; Paul, 2011). The metagame is defined as play beyond the mechanics of gameplay, consisting of opponent-centered strategy, use of out-of-game knowledge for in-game purposes, and peripheral content that facilitates alternate approaches to gameplay (Carter et al., 2012; Paul, 2011). MMO players attempt to make sense of their situations and improve their skills not just in terms of the game's mechanisms, the orthogame, but also in terms of playing with and against other players, the metagame, both of which are separate sets of skills, each with different training needs (Carter et al., 2012; Hoffman, 2013). For instance, playing poker requires learning the rules and procedures of the game (the orthogame) as well as the ability to 'play the players' (the metagame). These skills are interrelated but distinct (Carter et al., 2012).

Much like the separation between the mechanical and social play of poker, the delineation between orthogame and metagame is a critical distinction for MMO behavior research (Carter et al., 2012). Skills acquired from previous gameplay can influence users' behavior, so players' domain specific knowledge must be ascertained to avoid conflating skilled players with their less skilled counterparts (Schrader & McCreery, 2008; Phillips, Klein, Sieck, 2004). The field of research on behavior in MMOs includes a rich examination of performance-oriented research, which emphasizes orthogame skill, but does not include any metagame knowledge or accomplishments since performance alone is insufficient to measure metagame interactions among players. Orthogame measurements can be acquired from the user—through self-reports of efficiency, time-on-task, and expertise—or directly from an MMO Company's server records—noting economic status, achievements, equipment value, and other character information (Lewis & Wardrip-Fruin, 2010; Shim, Sharan, & Srivastava, 2010; Shim et al., 2011; Taylor et al., 2011; Wang et al., 2011). Even studies that discuss metagame information—i.e. Huffaker et al. (2009) evaluating the relationship between achievements and meta-expertise, Caplar, Suznjevic, and Matijasevic (2013) discussing player use of design flaws to further their in-game goals, and Reeves et al. (2009) emphasizing the importance of team-on-team strategy—focus primarily on orthogame measures and the interactions between the players and the game environment. Metagame ability, concerning interactions between players, requires the use of knowledge and skills that are not exclusively taught through the orthogame, so the assessment of this ability requires the measurement of different factors (Carter et al., 2012). This distinction between orthogame and metagame, however, is rarely discussed in MMO player behavior research and discussion about the need for non-performance-based measures is rarer still.

1.2. Data collection in the MMO behavior literature

MMOs provide an opportunity to evaluate players' progression as they learn to play the orthogame and a means to examine how they learn to interact with other players in the metagame during this time period (Carter et al., 2012; Steinkuehler, 2004). Research on MMO player behavior tends to emphasize players' orthogame experience, hence the methodologies are frequently characterized by the measurement of time spent pursuing in-game tasks that reward effort and players' performance efficiency (Bosser & Nakatsu, 2006; Reeves et al., 2009; Schrader & McCreery, 2008; Taylor et al., 2011; Wang et al., 2011). The methods by which performance and expertise are typically evaluated include time measurements during gameplay, action efficiency, exceptional combat performance, and skill and knowledge of game interfaces and mechanics (Huffaker et al., 2009; Reeves et al., 2009; Shim, Ahmad, Pathak, & Srivastava, 2009; Taylor et al., 2011).

To obtain this performance information, recent research into user behavior in MMOs tends to follow one of two general methods. One approach is the use of participant mediated data acquisition. Specifically, users are asked to provide details regarding their background characteristics, behaviors, aggregated gameplay time, level of expertise, gaming biography, and other relevant topics, using demographics, structured interviews, or self-reported measures (Chen, Duh, & Ng, 2009; Davis, 2002; Taylor et al., 2011; Quandt, Grueninger, & Wimmer, 2009; Reeves et al., 2009; Wolf, 2007). Participant-mediated measures of performance, such as surveys or interviews, require participants to estimate their activities over the course of weeks or even months, and thus are vulnerable to recall and response biases (Prince et al., 2008). In response to these issues, many researchers select the second general approach, in which player information is obtained directly from the game's server (Lewis & Wardrip-Fruin, 2010; Shim et al., 2011). MMO servers record an enormous amount of information on player behaviors, which allows an accurate measurement of player efficiency, game-driven performance, and duration of play time, thus avoiding the problems associated with the self-report measures (Bosser & Nakatsu, 2006; Taylor et al., 2011; Reeves et al., 2009; Wang et al., 2011). However, this second method focuses exclusively on the actions of the player character without considering the role of the player. Knowledge, attitudes, feelings, and factors outside the scope of the MMO environment are neglected. While both of these methods define the users' experiences, the former provides potentially biased self-report measures and the latter neglects the role of the player in-game behaviors, with neither approach providing a full understanding of expertise in MMO gameplay.

Server-side data collection does not provide any details about the individual human player in MMOs, creating an unnecessary separation between the avatar and the human that operates it. MMO players are a heterogenous group, varying by nationality (Xiong, 2012), disability status (Lim & Nardi, 2011), and age (Pearce, 2008). When relying solely on server-side statistics that only record the characteristics of the player's character, many of the details that noticeably differentiate different groups of players are obscured and player population seems more homogenous than they may be. Studies using server-side statistics that have large sample sizes are likely to include important sub-groups of participants that cannot be differentiated in the analysis of the more homogenous-seeming server side data. This obfuscation of player details is especially problematic when considering social learning and metagame expertise, because participation in a community of practice and interaction with other players is not captured by measures of game performance and efficiency. These player details are needed to adequately determine trends in player behavior. Simply put—individuals matter.

1.3. The problem: orthogame vs. metagame skills

In studies concerning player behavior in MMOs, expertise is frequently determined by several factors—e.g. play time (Chesney, Chuah, Hoffmann, Hui, & Larner, 2014), skill (Lewis & Wardrip-Fruin, 2010; Wang et al., 2011), account age (Caplar et al., 2013), character level (Huffaker et al., 2009), equipment ratings (Taylor et al., 2011), achievements (Wang et al., 2011), efficiency of play (Huffaker et al., 2009; Shim et al., 2009), tasks completion (Shim et al., 2011), firing accuracy (Caplar et al., 2013; Delalleau et al., 2012), number of character deaths, (Delalleau et al., 2012; Lewis & Wardrip-Fruin, 2010) and percentage of enemy encounters won (Caplar et al., 2013; Shim et al., 2009). While these data can be obtained from players via self-report measures, the acquisition of data from a game server provides significantly more objective, detailed information over a longer period of time (Delalleau et al., 2012; Shim et al., 2011). If expertise in an MMO was solely defined by a player's skill in using the game's interface to accomplish goals (i.e. the orthogame), the server-side data approach would be the most useful; however, as previously noted, a definition of expertise solely determined by performance, efficiency, and orthogame skill disregards major components of MMO expertise (Huffaker et al., 2009; Wang et al., 2011); by conflating such expertise with performance measures, researchers miss the socially collaborative interaction between players, the lack of which can hamper both the metagame and orthogame activities of players in MMO games (Debeauvais & Nardi, 2010; Reeves et al., 2009; Taylor et al., 2011). Thus, the individual differences among players affect their behavior during gameplay, and many of these differences are not captured through in-game performance. An initial step in detecting these differences among players is to develop assessment tools that differentiate members of a community of practice from those who do not participate in these communities.

In this study, we developed a knowledge assessment to evaluate player competence in the MMO community's shared repertoire of language and used it to establish membership in an MMO community of practice. Membership in a game's community of practice suggests a willingness to learn and improve, characteristic of expert performers (Ashton, 2009; Towne, Anders Ericsson, & Sumner, 2014). Experts approach gameplay and the challenges therein differently from a non-expert; while members of each of these groups may spend similar amounts of time playing the game, what they attain from that gameplay and what they do with that experience differs greatly (Phillips et al., 2004). Expertise, specifically whether or not players deepen their knowledge and expertise by sharing it with both newer players and their peers, is one of these underutilized areas of differentiation in MMO research (Ashton, 2009). Prior research on expertise can serve as a guide in the categorization of these players.

2. Expertise

2.1. Sensemaking and developing expertise

The term *expert* refers to an individual who has achieved exceptional skill in a particular domain (Phillips et al., 2004). This exceptional skill manifests in performance, characterized by consistency, accuracy, and efficiency, which can be produced with limited preparation (Ericsson, 2008; Phillips et al., 2004). Within their respective domains, experts exhibit a breadth and depth of knowledge, which affords them more inclusive mental models, greater repertoire of recognized patterns, more discriminating perceptual skills, wider variety of effective responses to situations, and greater declarative knowledge relative to their less knowledgeable counterparts (Eraut, 2000; Ericsson & Kintsch, 1995; Phillips et al., 2004).

In a particular MMO game, the acquisition of this knowledge is acquired through gameplay. Players have continually engaged in a sensemaking process, in which they have experimented with the designed experience of the orthogame, and through a process of trial and error, they have developed tacit knowledge of the rules of the game world and tacit procedures to respond to these rules (Carter et al., 2012; Eraut, 2000; Ward, 2010). As players progress through an MMO, they gain greater familiarity with its intricacies, developing complex mental models and caches of prototypical situations corresponding with desired outcomes (Andersen et al., 2012; Schrader & McCreery, 2008). Players elaborate or reframe these mental models as they are confronted with challenges and situations within the game, and they gradually acquire and use skills needed to progress to higher levels of play within the game

(Cannon-Bowers & Bowers, 2008; Eraut, 2000; Shim et al., 2009; Shim et al., 2010).

2.2. Automaticity and deliberate practice

In an MMO game, gameplay includes quests, which are focused bursts of goal-driven gameplay that users embark upon for rewards; the repetitive nature of these tasks leads users to practice certain orthogame skills quite often (Doran & Parberry, 2011; Schrader & McCreery, 2008; Wang et al., 2011). After frequent repetition, consistently adequate performance can be produced automatically, with little preparation required; the explicit procedural knowledge needed to accomplish this task becomes increasingly tacit, unspoken but used to inform behavior (Eraut, 2000; Ericsson, 2008; Keith & Ericsson, 2007).

Experts continuously seek new goals, higher performance standards, and more challenging situations in order to develop increasingly stronger skills and more complex mental representations (Ericsson, 2008; Keith & Ericsson, 2007; Phillips et al., 2004). This effortful training at the limits of one's ability with the explicit goal of improving a particular aspect of performance is known as *deliberate practice* (Keith & Ericsson, 2007; Towne et al., 2014). To successfully improve one's skill through deliberate practice, the individual requires a task with a well-defined goal, motivation to improve, meaningful feedback, and opportunities for repetition and refinement (Ericsson, 2008). MMOs provide players with these tasks in the form of quests (Doran & Parberry, 2011; Towne et al., 2014). As players gain levels and the game increases in difficulty, players attempt to complete progressively more difficult quests; thus, players maintain engagement and continue in a designer guided regimen of deliberate practice (Doran & Parberry, 2011; Schrader & McCreery, 2008; Shim et al., 2009; Towne et al., 2014).

As previously established, the orthogame presents the player with progressively more difficult challenges, up to the point where many quests or dungeons are too difficult to be tackled alone (Ducheneaut, Yee, Nickell, & Moore, 2006; Towne et al., 2014). At this point, users have a choice; they can either repeat the orthogame tasks that they have already completed, "grinding" monotonous tasks to achieve higher levels, or they can group with other players to complete the quests and dungeons they could not feasibly complete on their own (Ducheneaut et al., 2006; Hennig, 2013; Lu, Shen, & Williams, 2014).

If the player chooses the first option, until the orthogame is expanded, players would return to the previous challenges, until their performance reaches an asymptotically high level. Challenging situations are then no longer sought and improvement ceases, culminating in *grind* (the repetition of basic actions for an in-game reward, Hennig, 2013; Towne et al., 2014). Individuals typically seek to reach this level of consistent, adequate performance with routine tasks, such as driving or tying one's shoelaces (Ericsson, 2008; Phillips et al., 2004). However, routine tasks, especially in games, eventually lose their attractiveness; for instance, one study reported that 40% of surveyed World of Warcraft players stopped playing the game for six months or a year (Debeauvais, Nardi, Schiano, Ducheneaut, & Yee, 2011; Hou, Chern, Chen, & Chen, 2011).

Upon reaching the difficulty threshold, if players choose the second option and group with other players to pursue more difficult challenges, they are confronted with the need to exercise metagame skills (Carter et al., 2012; Ducheneaut et al., 2006; Lu et al., 2014). Metagame skills are needed to succeed in higher levels of play. Development of metagame skills, such as teamwork and knowledge of popular play styles, are often neglected by players who focus on the orthogame, and these players often engage in these activities only after they have finished gameplay. Thus, players who focus on orthogame activities may not have reached the appropriate level of expertise to accomplish their desired metagame goals (Carter et al., 2012; Ducheneaut et al., 2006; Guthrie, Reuter, Barkdoll, & Hexmoor, 2014; O'Connor & Menaker, 2008). As players develop their metagame skills, they recognize patterns amongst other players and within the game itself, establish expectations from the game and the other players within it, and develop strategies to take advantage of these patterns (Carter et al., 2012; Smith, Lewis, Hullett, Smith, & Sullivan, 2011). Expert players are characterized as individuals who possess a large repertoire of these patterns, which can be used to interpret complex situations and detect anomalies (Phillips et al., 2004).

2.3. Skill retention and sharing

MMO designers are particularly concerned with member account cancellation and player churn due to the sheer number of competing games their audience can choose (Debeauvais et al., 2011; Hou et al. 2011). The players' experience with previous games as well as competing games currently being played influences their knowledge and expectations of the new game, facilitating comparisons between games and reducing the difficulty in understanding the new game (Arsenault, 2009; Bartle, 2004, pp. 700–701; Hou et al., 2011). This breadth of experience allows players to expand their repertoire of game-related patterns, facilitating their development of expertise (Phillips et al., 2004).

Players, when confronted with a novel situation, try to interpret it by identifying similarities between what is known and what is new, in a process known as *analogical reasoning* (Bartle, 2013; Reeves & Weisberg, 1994). Players' metagame experience from previous, MMOs provide a familiar model to help solve similar metagame challenges in other MMO games. Each game that the individual successfully navigates results in an expansion of the metagame strategies they have available; these strategies can be used to deal with similar challenges across games despite differences in their respective orthogame characteristics (Arsenault, 2009; Ashton, 2009; Kim, Park, & Baek, 2009; Reeves & Weisberg, 1994; Ward, 2010; Xanthopoulou & Papagiannidis, 2012).

MMO games and metagame skills are not gained only through previous experience, however; they also have a strong social component. Players attempting to improve metagame skills must communicate with other players to gain needed information about trends, strategies, and styles (Carter et al., 2012; Steinkuehler & Williams, 2006). Information acquired through experience in the game can be effectively communicated to other players through the in-game chat system or out-of-game discussion spaces; this information transfer process induces players to reflect on and articulate the tacit knowledge they gained through experience, transforming it into explicit knowledge which they can share (Ashton, 2009; DeSanctis et al., 2003; Eraut, 2000; Kong & Kwok, 2009). To communicate knowledge gained through experience, the information must be translated into a common language and communicated either directly to other players (Ashton, 2009; DeSanctis et al., 2003; Eraut, 2000; van Harmelen, 2008; Wenger, 2000).

Research that measures expertise using only mastery of game mechanics, optimization of task completion, and in-game performance measures overlooks the tactical and strategic interplay of cooperative and competitive play, knowledge shared among players, and other community-oriented metagame activities (Caplar et al., 2013; Reeves et al., 2009; Shim et al., 2009; Taylor et al., 2011; Wang et al., 2011). Given that an MMO player's expertise extends beyond efficiency of orthogame skill, MMO researchers should reorient their thinking away from models based only on game performance, as is useful in single-player games, towards a model that defines expertise using *both* game performance and community established expertise in the metagame (Shim et al., 2009; Taylor et al., 2011).

3. Membership in a game community

The primary difference between a traditional video game and an MMO is that the latter is consistently populated by other players. MMOs facilitate communication between players through the use of synchronous and asynchronous communication mediators (Schrader & McCreery, 2008; Steinkuehler & Williams, 2006). Using synchronous communication mediators, such as the chat functionality or through avatar-mediated communication, players communicate with one another or are witness to those communications (Castronova, 2001; Steinkuehler, 2004). Outside of the game space, players build social objects to construct, revise, and share mental models with other players asynchronously (DeSanctis et al., 2003; van Harmelen, 2008). Through the use of these mediators, players gain a convenient way to gain knowledge without having to experience it first hand, or a way to transmit hard-won information to the less experienced. Players' shared interest in the online world, their joint activities, and their communication with one another are indicative of participation in a community of practice (Ashton, 2009).

3.1. Communities of practice

Communities of practice are groups of people who share interest in a domain, and further each other's' understanding through continuous, mutual engagement (Wenger, 2000, 2006). These communities are characterized by knowledge generation, promotion of shared understanding, and frequent social interaction over a common ground (DeSanctis et al., 2003; Wenger, 2000). Communities of practice centered around MMOs tend to feature robust online communities who communicate through online forums, discussion boards, and chat rooms, as well as within the game itself (DeSanctis et al., 2003; Lehdonvirta, 2010; Steinkuehler, 2004). Within these communities, members share mental models and best practices used to accomplish goals in relation to the relevant MMO game; participation in this community can, henceforth, be associated with knowledge to which non-community members may not be privy, a group Wenger (2006) referred to as practitioners (DeSanctis et al., 2003; Wenger, 2006). An established community of practice can define the prerequisites necessary to be perceived as competent, but it can be used to also identify expertise amongst its members (DeSanctis et al., 2003; Eraut, 2000). Even the most objective orthogame approach, i.e., analysis of server-side player data, cannot measure the socially determined competences and prior experiences of these practitioners (Ashton, 2009; Lewis & Wardrip-Fruin, 2010; Shim et al., 2011; Taylor et al., 2011).

These communities of practice can identify the competence displayed by its members' through their participation in the community; this can be defined through a combination of three elements: joint enterprise, mutuality, and shared repertoire (Wenger, 2000, 2006). To be competent in regard to joint enterprise, a member must understand what the community is about and be able to contribute to that community (Wenger, 2000). To be competent in regard to mutuality, a member must be engaged with the community and establish a trustworthy reputation (Wenger, 2000). Finally, to be competent in regard to shared repertoire requires the production or use of communal language, artifacts, tools, and stories (Wenger, 2000). Players exhibiting competence in these three elements are demonstrating their capability as a practitioner, as determined by the social standards used for assessing competence of those participating in the community of practice (Wenger, 2000, 2006).

MMO communities, in their shared repertoire, use a number of artifacts and tools—such as forums, streaming video channels, message boards, and collaborative websites where members edit the content (wikis)—as mediators in their communication with other community members (Baird & Fisher, 2005; Hamilton, Garretson, & Kerne, 2014; Lehdonvirta, 2010). Use of these tools provide players with the opportunity to gain more information, share their experience, build community, and provide overall support for the process of collective sensemaking (Schrader & McCreery, 2008; Stigliani & Ravasi, 2012; Wenger, 2000). Players create and maintain these socially generated artifacts so that they can be used to communicate, often asynchronously, the information they have gathered, their interpretation of such, and the strategies they have developed (Stigliani & Ravasi, 2012; Wenger, 2000).

These community edited repositories of knowledge allow players to build and share mental models of the game through a process of social constructivism. The social constructivist learning paradigm suggests that learners build knowledge through social interaction, and subsequently that social networking tools and services are artifacts that can mediate this communicative learning process, even amongst players who are no longer active in the game itself (Baird & Fisher, 2005; van Harmelen, 2008). When interacting with other community members, players communicate by networking these artifacts together, with users of one artifact referencing information found in others, creating a density of information that requires a firm understanding of that community's shared repertoire (Galarneau, 2005; Wenger, 2000).

Peer nomination has been frequently used in the past to identify experts in a field, and while nomination alone is subject to error, an emphasis on deliberate practice of domain related activities and participation in the three aspects of a community of practice will better allow us to identify expertise in MMO player populations (Ericsson, 2008; Phillips et al., 2004). The community-established means of determining expertise, especially the use of shared repertoire, is a distinct, viable means of distinguishing between engaged community members and those who are less engaged by accounting for factors beyond physical skill and time on task.

3.2. Importance of expertise and community of practice to MMO behavior research

As we have previously established, variability in the characteristics of individual users is important for understanding variability in MMO behaviors. MMO game players, even in a single MMO game, are a very heterogeneous group. The aggregation of in-game player behavior data, to the extent that players can be considered a single group, cannot detect the numerous factors that underlie player heterogeneity. One of these factors is player metagame expertise, which we argue is expressed through participation in a community of practice. A focus on players, contextualized within a community of practice, rather than a demographic or in-game performance data approach, affects selection of research methodology concerning MMO behavior. To better contrast the performance and demographic approach to player expertise evaluation with a more player-oriented approach, we briefly consider the differences in how data is collected, how player and skill retention is approached, and how robust individual player skill and larger community information are against constant change in the domain.

3.3. Data collection in the MMO domain

The collection of performance data through server-side data collection provides a plethora of objective, continuous data concerning player behavior regarding avatar performance in the orthogame. While the data obtained via this method accurately reflect user action, those data are limited to player performance alone. As we have established, player behavior is influenced by player expertise, which extends beyond player performance. This collection of essentially observational data immerses the researcher in player statistics, often leading to massive sample sizes (Caplan, Williams, & Yee, 2009; Debeauvais et al., 2011; Delalleau et al., 2012). Unfortunately, the large sample sizes attained through server-side data collection do not reduce heterogeneity in the expertise of the individuals who comprise the sample. Consequently, in contrast to studies with random assignment to groups, an increased sample size does not reduce the impact of unobserved biases, which occurs when an important variable is omitted from a model (Rosenbaum, 2005). Specifically, the server-side data collection method ignores the relevant knowledge and metagame experience of the individual user, instead using large sample sizes to aggregate players, treating them, analytically, as samples from a single population.

Many studies that use a demographics approach also amass large sample sizes, but only focus on player performance and common demographics (Hou et al., 2011; Schrader & McCreery, 2008; Yee, 2006). Demographic attributes—such as age, gender, and education level—can influence players' in-game behavior, but the usefulness of such information depends on how the target population is sampled (Quandt et al., 2009; Xiong, 2012). If the sample is determined by convenience or participant self-selection, the demographic information of this sample may not reflect differences that appear in the larger population (Quandt et al., 2009). Large online surveys about player performance, as they are often used, introduces the disadvantages associated with self-report data, while simultaneously lacking the benefit of communicating with individual users by overlooking individual differences and targeted sampling of players.

The importance of identifying individuals with metagame skills within a given sample coupled with the growth of members' expertise in communities of practice indicates the need to capture information about players and their metagame experience. The acquisition of MMO player performance data from a game server is useful and should be encouraged, but researchers should also evaluate domain knowledge and membership in a community of practice. This dual approach harnesses the strength of server-side performance measures, which provide data concerning player performance and efficiency metrics, with the strengths of an individual-focused study, such as ascertaining knowledge and practices of individuals. Focusing on identifying membership in a community of practice should facilitate more accurate evaluation of player expertise than performance-oriented measures.

3.4. Retention in the MMO domain

Few MMO players only have experience with a single game. People who currently play an MMO have likely played other MMOs in the past, and may even be playing multiple MMOs concurrently (Hainey, Connolly, Stansfield, & Boyle, 2011; van Meurs, 2007). Players leaving a game, often for a competing product, is such a concern that an entire area of research, referred to as *churn analysis*, has emerged to better understand the factors that influence this player behavior (Debeauvais, Lopes, Yee, & Ducheneaut, 2014; Kawale, Pal, & Srivastava, 2009). Exclusively measuring performance in a single game prevents the exploration of factors that set apart a game from its competitors and thus prevent churn.

Even if the game in question is the player's primary MMO, experience with prior MMOs can color a player's approach to and performance in the new game, due to analogical reasoning (Ashton, 2009; Hou et al., 2011; Reeves & Weisberg, 1994; Smith et al., 2011). Server-side data studies, limited to a single game, overlook the influence that experience with other games can have on players' actions; previous knowledge, behavior, and achievements in a game are highly predictive of players' future actions in a different game (Harrison & Roberts, 2011). Hence, research that focuses on a single game neglects any skill or knowledge retention from previous games.

Many MMOs, especially those in the same genre, may share familiar elements, or even the same game engine; however, they usually differ in terms of interface design and avatar capability (Arsenault, 2009). These differences influence a player's play style and the strategies they use to achieve efficient performance, thus leading to seemingly similar games having a very different orthogame. These differences limit the extent to which orthogame training from other games can be applied to any other particular game. However, as players recognize patterns within the game and develop strategies in response to these patterns, they develop expectations about the game. These expectations are communicated through the player community, and to game developers observing the player community, all of whom carry these learned lessons with them as they move to other games (Smith et al., 2011). Consequently, developers build new games and players approach these new games with these shared expectations in mind, as derived from reactions to the game and other players. For example, 'stealthy movement' is an approach to gameplay that is inherent to certain games, but can be implemented in others, creating *stealth friendly* levels in games across multiple genres (Tremblay, Torres, Rikovitch, & Verbrugge, 2013). Developers depend on observation of players and playtesting to produce content that feeds into player desires and expectations, improving player retention and mitigating churn (Hadiji et al., 2014; Moura, el-Nasr, & Shaw, 2011; Swain, 2008). Hence, the impact that a game's community of practice can have on their players and future gameplay necessitates the examination of a player's participation in that community.

3.5. Robustness in the MMO domain

The field of MMOs is constantly changing, with new games emerging into the marketplace, and older games updating and expanding their content offerings. Players must adapt to changes in the orthogame that result from new content and modified game mechanics as well as changes in the metagame that stem from other players exploring and utilizing these orthogame changes to best effect against other players. While only the game developers can change the orthogame, potentially any player can revise the metagame, by developing a strategy that gains popularity or instructing other players on how to use a game exploit. As MMOs constantly change both orthogame and the metagame characteristics, and players are exposed to multiple games with overlapping communities, contextual performance measures recorded in an MMO today may not be entirely relevant in future manifestations, in which the orthogame and metagame have changed.

Evaluations of player performance are limited to the specific version, or 'build,' of the MMO used during the assessment, as player performance is constrained by the characteristics of that specific version; for example, performance data from World of Warcraft in 2010 may not be applicable to data for that game in 2014. Evaluations of the metagame, based on knowledge, are more robust to developer change, given that knowledge is less likely to be rendered obsolete by a sudden change in the MMO content. Metagame information is more vulnerable, however, to influences from other games' communities of play which may have overlapping player populations.

4. Measurement of metagame knowledge

Considering the members of these game-oriented communities as participants in an MMO community of practice implies both that they possess shared mental models and that best practices are disseminated through this community; membership, therefore, corresponds to a certain level of domain knowledge. As members of a community of practice, users must demonstrate skill in three dimensions to be deemed competent by the community (Wenger, 2000). Competence displayed through 'joint enterprise' and 'mutuality', implies action on behalf of the user, and hence may require observation of that user within a community. By contrast, 'shared repertoire', due to its emphasis on knowledge and the usage of intermediary artifacts (e.g. language) can be examined separately from the community from which it emerged (Ashton, 2009; Wenger, 2000). The vocabulary used in MMOs originated as adaptations from table-top gaming and software specific terms, subsequently evolving into a uniquely MMO oriented vocabulary (Norlin, 2013). For instance, terms such as 'mob,' a truncation of 'mobile' originates from the MUD (Multi User Dungeon), an early, text-based persistent virtual environment (Bartle, 2004; Yee, 2005). While many current users may have no direct experience using MUDs, the MMO community they inhabit was concurrent with MUDs; consequently, participation in the community of practice necessitates competence with the terminology used in the community to communicate with other members, with the result that new players 'inherit' terms from prior games (Taylor et al., 2011). Proficient use of the relevant lexicon demonstrates competence to others within the community of practice, bolstering the user's reputation as a skilled player among other community members (Steinkuehler & Williams, 2006; Taylor et al., 2011; Wenger, 2000). The scope of the present investigation is limited to participants' lexical knowledge as such knowledge is a foundation of competence building in a community of practice.

Given that a common language is part of the shared repertoire used by a community of practice, we believe that an assessment of participants' competence with this domain-specific language can be used to identify practitioners within the population sampled and distinguish them from non-practitioners (Wenger, 2000). To serve this end, we have developed an evaluation of participants' knowledge of MMO specific language, which we call the MMO Domain Familiarity Evaluation (MDFE). The terms we used in the evaluation have all been used in studies of user behavior in MMOs and they have been selected for their applicability to multiple MMO games.

The MDFE should provide a method to distinguish MMO users, who are actively engaged in deepening their expertise in this area as practitioners, from their less engaged counterparts within a sample. An individual with a demonstrable competence in the shared vocabulary of the community will have invested the time and effort needed to attain practitioner status, while non-practitioners would not have been exposed to the same experiences, and consequently would have greater difficulty understanding the language (Wenger, 2000, 2006).

4.1. Current study

For the present investigation, we tested the effectiveness of two models for distinguishing practitioners from non-practitioners. Model 1 consisted of traditional demographics variables used in previous research, specifically: age, sex, and age at which the individual began playing video games. Model 2 consisted of variables such as: number of genres played, number of MMO hours played per month, and Videogame Self-Efficacy score. Hence, we tested the following hypotheses in the current study:

H1. : Both Model 1 and Model 2 should predict membership status as measured by MDFE score.

H2. : A model using demographic questions focusing on interaction with other players (i.e. Model 2) will be a better predictor of membership in a community of practice, as determined by the MDFE, compared to a model comprised of demographic measures traditionally used in MMO behavior studies (i.e. Model 1).

In summary, upon establishing the MDFE as a means of distinguishing membership in one of these two groups, which analyses of server-side data cannot, we compare demographic questions traditionally used in MMO behavior studies with more gaming behavior-specific questions to determine if the models are predictive of membership (Hypothesis 1), and if the gaming specific model more accurately identifies sampled users as members of a community of practice (Hypothesis 2).

5. Methods

5.1. Participants

We recruited 552 participants (293 men and 259 women), from a large university in the southern United States, who volunteered via an online system in exchange for course credit. Data from 13 participants were incomplete or showed evidence of non-compliance with survey instructions (e.g. marking all answer choices "C" or having response times exceeding ± 3 *SD* of the mean); therefore, data from 539 people (285 men and 254 women) ranging from 18 to 53 years of age ($M_{age} = 21.15$; $SD_{age} = 4.68$) were analyzed in this study. All participants were college students with an average of three years of education since high school ($SD = 2.85$). A majority of the participants reported that they played MMO games (441 players and 98 non-players). Participants who played MMO games reported playing, on average, two genres of games ($M = 2.27$, $SD = 1.52$), and playing MMO games on average of 24.09 h per month ($SD = 37.79$).

5.2. Materials and procedure

Participants completed the survey through Qualtrics, a web-based survey management system. All participants completed the following surveys: Demographics, self-reported Videogame Experience, Videogame Self-efficacy (VGSE; Pavlas, 2010), and the knowledge assessment (i.e. the MMO Domain Familiarity Evaluation; MDFE). The Demographics solicited—age, sex, years of education—are frequently used in other MMO studies to describe the population of MMO players. Self-reported Videogame Experience—age participants began playing video games, number of different game genres they have played, and number of hours per month they play MMO games—are used to enumerate players' experiences with MMOs in these studies. Videogame Self-efficacy, adapted from a generalized self-efficacy scale, is a series of 10 seven-point likert scales describing participants' self-efficacy toward situations in video games, whose sum provides a participants' VGSE score. The items in the MDFE, a randomized series of 54 multiple choice questions, were used to determine if participants could match common MMO definitions to their terminology. Participants were instructed to complete the surveys during a single session.

5.3. MMO domain familiarity evaluation

The MDFE was developed to confirm that participants understood the terminology used in the study (Oppold, Rupp, Lakhmani, & Szalma, 2013). Participants were asked to first read scenarios, derived from behavioral interactions described in the MMO literature, then they were asked to report their perceptions of each interaction's fairness, severity, and frequency. This manuscript examines our findings pertaining to the MDFE and the demographics of our sample, whereas future research will utilize the MDFE to examine the differences between the differentiated groups in regards to scenario based self reported measures of fairness, frequency, and severity.

The initial step in the development of the MDFE was to conduct an analysis of terms used in multiple MMO behavior studies, across game genres. From that gathering of terms, we developed 54 multiple choice questions pertaining to common vocabulary used in MMO games. We presented each of the 54 questions each with four possible answer choices (the correct definition and three distractors). Example questions are provided in Table 1. Knowledge test scores were computed by assigning each correct answer a score of '1' while incorrect answers were assigned a score of '0', with total score defined as the sum of all correct items answered by each participant.

6. Results

All analyses were performed using SPSS v.22. We derived each participants' MDFE score by summing all correct answers to all 54 questions ($M = 27.92$, $SD = 12.62$). A visual inspection of the data, suggested a bimodal distribution of participants' performance scores (Fig. 1). Additionally, z-scores for skewness and kurtosis were both greater than 3.0, indicating a substantial deviation from normality.

Due to the observed bimodal characteristics of the MDFE scores, the data were split into separate distributions (Xiong, 2012). Inspection of Fig. 1 indicates two modes, one at a score of 15, with a frequency of 30 participants, and a second at a score of 45, with a frequency of 28 participants. To distinguish the low scorers from the high scorers we employed a three step procedure. First, the data were divided into two groups separated by the median score (Mdn = 27). Second, we calculated 95% confidence intervals around the mean of each of the two resulting distributions and we saw no overlap between them. Finally, we removed participants outside of the upper bound of the CI of the low scorer group and the participants outside of the lower bound of the CI from the high scorer group to ensure that these two groups were isolated. We refer to this middle group as the "unassigned" group. These participants achieved scores in the range between both the low and high distributions, but given that their scores were outside the 95% confidence interval, their group membership is ambiguous. Participants with scores in the lower distribution were assigned to the 'low knowledge' group and those who achieved scores in the higher distribution were assigned to the 'high knowledge' group. We used confidence intervals to distinguish the two groups because they are noncentrality measures, which do not require probabilistic tests or a null hypothesis (Law & Kelton, 2007, pp. 270; 552–554; see Table 2). Note that the scores for the two groups identified by this procedure were each normally distributed. The original sample was fairly evenly distributed in the numbers of male and female participants, but dividing data in accordance to MDFE score resulted in a sex imbalance between the high and low scorers (See Table 2). However, while the two resulting distributions, absent the scores falling outside the 95% confidence intervals, were normal, the dichotomous outcome variable necessitated the use of logistic regression. Two separate models were evaluated by performing two logistic regression analyses based on the previously specified hypotheses. For each model, the dependent variable was membership in the 'high knowledge' or 'low knowledge' groups.

6.1. Model 1: the demographic model

The predictors for model 1 were four demographic variables commonly used in studies of MMO play: Age, Sex (0 = male; 1 = female), age started playing video games, and years of education; consequently, we shall refer to Model 1 as the Demographic Model. Data for all variables were obtained from a self-report demographics questionnaire completed by the participants. Five-hundred and thirty nine cases were included in the analysis. The variable 'years of education' did not prove to be a significant predictor of test score ($p = .23$), so it was omitted from the model and a three predictor model was tested. Consistent with expectation, the beginning block was only 50.1% accurate at predicting group membership as defined by test score. However, the model was significantly improved by the prediction variables, $\chi^2\ (3) = 90.87$, $p < .001$) and the success rate of the model was raised to 69.40%, partially confirming Hypothesis 1. Model fit was assessed using a Hosmer and Lemeshow Test which was non-significant, indicating that there were no deviations from the observed and expected frequencies across the data, $\chi^2\ (8) = 9.86$, $p = .28$. Nagelkerke R^2 indicated that 21.90% of the variance in test score was predicted by the model. The regression coefficients, Wald statistics, odd ratios, and 95% confidence interval for odds ratios for each of the three predictors are summarized in Table 3. According to the Wald criteria, Sex was the most reliable predictor, $\chi^2\ (1) = 76.05$, $p < .001$. Holding all else constant, the impact of being a man is positive, increasing the odds of being in the high scorer group by 578% (Exp(B) = 5.78). There was a greater number of male participants in the high scorer group (72.7%) than in the low scorer group (32.7%).

Participants' age was the next most reliable predictor, $\chi^2\ (1) = 6.11$, $p = .013$. Increasing participant age by one year increased the odds of being in the high scorer group by 107% (Exp(B) = 1.07). The Age started playing video games ($p = .095$) variant was only marginally significant, indicating that it did not contribute substantial predictive power to the model.

6.2. Model 2: the experience model

Our first model, using only basic demographic information was consistent with Hypothesis 1. We next evaluated the predictive ability of community of practice specific demographic information.

Table 1
Example questions from MDFE. Correct answer are denoted by an asterisk.

Question	Answer A	Answer B	Answer C	Answer D
These are specific rewards for killing monsters and completing quests, which are added to the total value for the character, and in some games, these can be reduced if the character dies.	Experience	Quest items	Loot	Experience Points*
This is when status effects or enchantments are removed from the target for the purposes of making the target weaker	Buff	Debuff*	Status Effects	Enervate
These are unique enemies, which are more powerful than other enemies, appear less frequently or only under specific conditions, but do give rare or powerful rewards.	Bosses*	Elites	Sergeants	Higher Level

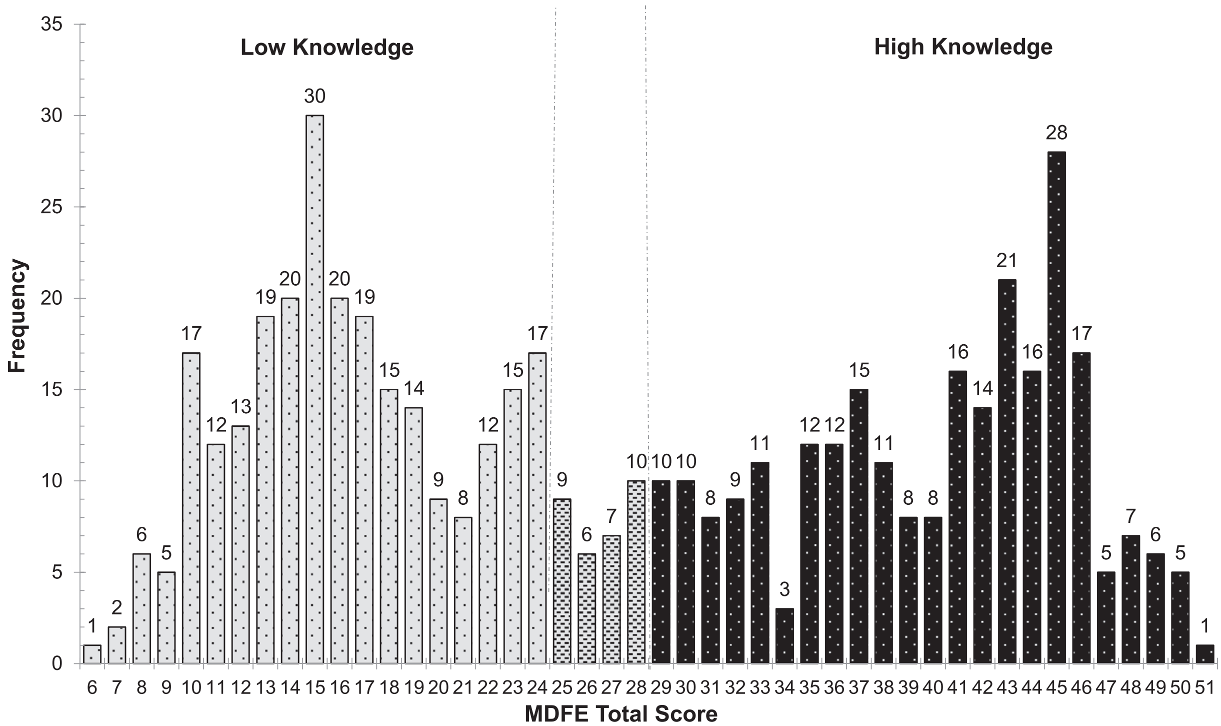

Fig. 1. Frequency distribution of MDFE. Dotted vertical lines denote 95% confidence intervals of split distributions. Lighter bars indicate assignment to low score distribution, darker bars indicate assignment to high score distribution, bars outside.

Table 2
Descriptive information of MDFE score distributions. Some scores left unassigned due to falling outside the 95% confidence interval.

	MDFE score			Age (*M* [*SD*])	Gender		Age started VG play (M [SD])	Number of MMO genres played (*M* [*SD*])	MMO hrs./mth (*M* [*SD*])	VGSE (*M* [*SD*])
	M (*SD*)	95% CI of the mean	*Mdn*		Men (*n*)	Women (*n*)				
Original distribution ($n = 539$)	27.93 (12.62)	26.82; 28.99	27	21.15 (4.68)	285	254	8.43 (4.65)	2.27 (1.52)	24.09 (37.79)	8.96 (2.60)
Low Knowledge ($n = 254$)	16.11 (4.49)	15.56; 16.66	16	20.89 (4.11)	83	171	8.78 (5.14)	1.73 (1.51)	7.11 (15.72)	16.11 (4.49)
Unassigned ($n = 32$)	26.56 (1.22)	26.12; 27.00	27	23.81 (7.44)	18	14	9.50 (6.00)	2.21 (1.52)	17.31 (36.04)	9.72 (2.02)
High Knowledge ($n = 253$)	39.95 (5.78)	39.23; 40.66	41	21.07 (4.71)	184	69	7.94 (1.33)	2.82 (1.33)	41.99 (44.89)	10.35 (1.64)

As in the first model, the second model used MDFE score to assign membership to one of the two groups (0 = low; 1 = high). This dichotomous outcome measure was regressed on three predictor variables: Number of MMO genres played, Number of hours of MMO games played per month, and VGSE score; we shall refer to Model 2 as the Experience Model. As stated in Hypothesis 2, these variables were expected to be stronger predictors than the variables used in the demographic model.

Again, the initial block was only 50.1% accurate at predicting group membership based on test score. However, the three predictor variables significantly improved model prediction, χ^2 $(3) = 261.11$, $p < .001$) and the success rate of the model was increased to 79.70%. Model fit was assessed using a Hosmer and Lemeshow Test, which was non-significant, indicating that there were no deviations from the observed and expected frequencies across the data, $\chi^2\,(8) = 7.68$, $p = .465$. Nagelkerke R^2 indicated that

Table 3
Logistic regression statistics for model 1, the demographic model, and model 2, the experience model.

Model	Variable	B	S.E.	Wald	df	EXP(B)	95% CI for EXP(B)	−2 LL	R^2_N	R^2_{CS}
Model 1	Constant*	−1.95	0.54	13.02	1	0.143	–	611.98	0.219	0.164
	Age*	0.064	0.026	6.11	1	1.07	[1.01; 1.12]			
	Sex**	1.76	0.202	43.05	1	5.79	[3.91; 8.60]			
	Age started VG	−0.04	0.024	2.79	1	0.96	[0.92; 1.01]			
Model 2	Constant**	−5.22	0.568	84.61	1	0.005	–	441.74	0.537	0.403
	Number of genres played*	0.188	0.084	5.09	1	1.21	[1.03; 1.42]			
	Number of MMO hours/month**	0.042	0.007	36.96	1	1.043	[1.03; 1.06]			
	VGSE score**	0.445	0.06	55.85	1	1.561	[1.40; 1.76]			

Note: $^*p < .05$; $^{**}p < .001$, Sex was coded 0 = male; 1 = female.

53.70% of the variance in test score was predicted by the experience model. Consistent with hypothesis 2, the experience model was a stronger predictor of group membership than the demographic model.

Table 3 summarizes the regression coefficients, Wald statistics, odd ratios, and 95% confidence interval for the odds ratios for each of the three predictors. According to the Wald criteria, all three predictors significantly contributed to the model. VGSE, χ^2 (1) = 55.85, $p < .001$, number of hours played per month, χ^2 (1) = 36.96, $p = .001$, number of genres played, χ^2 (1) = 5.09, $p = .024$, were respectively the strongest predictors of group membership. Individuals in the low scorer group played an average of 1.73 (SD = 1.51) MMO genres, played an average of 7.11 ($SD = 15.71$) hours per month, and achieved an average VGSE score of 7.47 ($SD = 2.62$). Individuals in the High scorer group played an average of 2.82 ($SD = 1.33$) MMO genres, played an average of 41.99 ($SD = 44.87$) hours per month, and achieved an average VGSE score of 10.35 ($SD = 1.64$). The odds ratios indicate that, holding all other factors constant, the odds of being in the high scorer group increased by a factor of 1.21 for each additional genre played, 1.043 for each additional hour of MMO games played per month, and 1.56 for each additional score point on the VGSE scale.

7. Discussion

Members of a community of practice expand their knowledge of the domain through deliberate practice, a pattern of behavior that is both required for the acquisition of expertise and is predictive of skilled performance (Ericsson, 2008; Towne et al., 2014). Expert performance stems from the development of complex mental representations, a coherent narrative established by sensemaking, that can be established, developed, and shared with others in a community of practice (DeSanctis et al., 2003; Ericsson, 2008). In a community of practice, access to these shared mental representations require a level of domain knowledge sufficient to access and successfully use that community's shared repertoire (Schrader & McCreery, 2008; Wenger, 2000). Our approach uses membership in a community of practice to differentiate practitioners within a population according to their domain knowledge.

We used participants' knowledge of the community's shared repertoire of language, as measured by the MDFE, to evaluate their competence in this domain. Using this evaluation of competence, a metagame-oriented measure, contextualizes both the participants' response and any subsequent orthogame-specific measures (Ashton, 2009; Carter et al., 2012). We used the MDFE to explore participant membership in a community of practice through an evaluation of their knowledge of the terminology used within this community. This approach avoids the limitation of self-report measures resulting from the ambiguity between players' self-identity and behaviors; for instance, players can subscribe to games for months without actively engaging in gameplay or with the game's community (Debeauvais et al., 2011). Using a specifically metagame-oriented assessment, we were able to identify a noticeable difference in domain knowledge among participants in the sampled population, which would not have been detected using only orthogame-specific measures.

The non-normal distribution of scores in the MDFE was consistent with our assertion that the MDFE assesses a portion of MMO domain knowledge, specifically membership as a practitioner in a community of practice. We identified two modes, at opposite ends of the distribution, which separated participants into two distinct groups, one representing high knowledge scores and the other representing low knowledge scores (see Fig. 1). The 95% confidence intervals of the distributions did not overlap, indicating a significant and substantive difference and confirming that there are two distinct groups. However, the presence of participant scores in the gap between the confidence intervals of the means for the distributions indicated that the precision of the MDFE measure was not sufficient to confidently assign all individuals in the sample to one of the two groups. These participants were therefore not assigned to either group. We tested the demographic and community of practice models relative to baseline models; both models successfully predicted membership in one of two groups, indicating that the groups, established by confidence interval comparisons, may represent membership in a community of practice.

Demographically, the sample was comprised of college students from a large Southeastern university, mostly first and second year students under the age of 21. Although the sample is therefore somewhat homogenous, our test for knowledge of MMO shared repertoire revealed the presence of two distinct populations represented in our initial, seemingly homogenous sample: individuals who can comfortably use the language of an MMO community of practice (practitioners) and those who cannot (non-practitioners). These results demonstrate that assessment of participation in a community of practice provides contextual information that can supplement data gained from the examination of server statistics, allowing player domain knowledge to be used to improve our understanding of player behavior. For studies gathering data from online meeting places (e.g., forums, message boards, and community portals), measuring participation in a community of practice can facilitate a more precise categorization of the heterogenous sample of people who participated in that online survey. Measures, such as the MDFE, can be used to differentiate practitioners in a community of practice from those less likely to be practitioners. Here, MDFE scores indicated that our sample was not homogenous with respect to membership in the MMO community of practice. Reliance on traditional demographic information would not have revealed the subpopulation of practitioners in the present study.

Previous studies modeling player behavior in an MMO, either through server statistics or self-report measures, generalize players based on performance, then attempt to ascertain differences based on general demographic data, such as age or sex (Wang et al., 2011). Using player efficiency, which presumes that player motivation is limited to maximizing performance, as the criterion for expertise does not take into account the differences in how player behavior can influence measures of performance and engagement in social-oriented tasks (Shim et al., 2009; Taylor et al., 2011). Membership in a community of practice, ascertained by a knowledge test, allows us to better predict whether players will engage in deliberate practice or inefficient behaviors, such as attempting tasks beyond their capabilities (Shim et al., 2009). This variety of behavior, beyond the pursuit of efficiency, suggests that player behavior may be more heterogeneous, even when obtained from homogenous populations (Taylor et al., 2011).

7.1. Model 1: the demographic model

MMO studies often use demographics obtained from a self-selecting sample; these studies often produce non-predictive factors or weak effects. Studies that have more vigorously controlled their population, examining a highly specific group with balanced age or gender sampling (Pearce, 2008; Xiong, 2012), do not support findings of the significant differences based solely on gender or age as seen in other studies lacking those controls (Chesney et al., 2014; Wang et al., 2011). Looking at practitioner status and participant sex, we observed two heterogeneous groups that emerged from a seemingly homogenous sample; more sampled practitioners were men, while more sampled non-practitioners were women. Like in some other MMO papers, sex was controlled overall, but an examination of sex distribution in light of community of practice membership revealed a hidden population difference. This difference may also exist in studies that were laid out similarly to this one, but did not evaluate membership in a community of practice. Furthermore, given the college population sampled, it is likely that the sample was homogenous with regard to age as well. Despite the relatively limited age range of the sample, we observed that age was predictive of practitioner status and merits further investigation within the exploration of membership in a community of practice. Using appropriate methodological control, we were able to use this demographic information, which is often used to describe players in MMO studies, to successfully predict membership in a community of practice, using MDFE score.

While the aforementioned demographic information can be used to predict practitioner status, we compared these demographics with a more domain specific set of behavior questions. In accordance with Hypothesis 1, both models were able to predict membership in these two groups, as measured by the MDFE, but the experience model was able to do so more successfully.

7.2. Model 2: the experience model

The experience model was able to explain more variance than the demographic model; this finding was consistent with Hypothesis 2. Furthermore, the factors used in the experience model were continuous, so we were able to use the predictive factors to acquire a more granular prediction of the probabilistic odds of a participant belonging to one group or the other. Given the aforementioned homogeneity of the demographic model and the greater explained variance of the experience model, we recommend that future MMO researchers use experience models rather than demographic ones when exploring differences in player knowledge and behavior.

We confirmed that the MDFE score yielded two distinct groups of participants, that these two groups could adequately represent membership in a community of practice, and that using a model focusing on domain specific questions is a more useful predictor of membership than a model focusing on general demographics. These results imply that determining membership in a community of practice may enhance the understanding of player behavior.

7.3. Applications and recommendations

The distribution of player scores in the MDFE suggests that there are two distinct populations, a low and high knowledge group. This knowledge difference, which corresponds to practitioner status in a community of practice, is often not explored in MMO studies. Consequently, data from participants outside the community of practice may contribute to noise in data collection, which would weaken effects and increase unsystemic variance. We recommend that researchers examine practitioner status in a relevant community of practice as a means of reducing noise in a populations sample; this practice will strengthen future research by providing greater scrutiny of the population samples.

While an assessment of domain knowledge, like the MDFE, has been used more successfully than traditional demographics to determine membership here, a variety of competence measures are available (e.g. teamwork skills in raids, speed in leveling new characters, and so on). The MDFE, by design, is a very broad measure of general MMO terminology, as determined by current literature. Studies using homogeneous or highly heterogenous samples should use competence measures, such as the MDFE, or domain specific questions based on participant behavior, such as those used in the experience model, to more effectually describe the sample. Both would be preferable to general demographics, which require samples that are sufficiently controlled.

If the sample is more homogenous with respect to a single game or genre, generalized demographics and more specific questions in the knowledge test would be appropriate, but the resulting data would thus be generalizable only to the designated population; i.e a knowledge evaluation of terms specific to World of Warcraft would be very appropriate for World of Warcraft players, but inappropriate to those who have not played that game, but still participate in other MMO genres, making the evaluation less applicable to assessments about all MMO players. A more heterogeneous sample, with a wider variety of knowledge, requires more specific demographics and more generalized questions. Cooke, Salas, and Cannon-Bowers (2000) describe heterogenous knowledge distributions in teams of doctors and nurses; specifically, while doctors and nurses can work together because they share common knowledge, both groups possess distinct scopes of knowledge. In essence, competence measures intended to differentiate membership of a community of practice should be developed based on participation in any MMO, specific MMO product, or the knowledge and practices encompassed by a set of MMOs in a genre.

7.4. Limitations

While this study explored a number of issues regarding methodological practices, this pursuit occurred with a number of limitations. The MDFE is a very broad, generic measure that fits all MMO play. Research that examines a particular MMO genre or individual product would be limited by the broad nature of the MDFE. These more specific examinations should instead utilize a similar knowledge based competency test that would further differentiate those participants who play that genre or product from those who play MMOs overall. A further limitation of the study is that the MDFE can be confused with a competency measure of participants within either group. While the MDFE assesses player knowledge, it can only be used to assess membership in a community of practice. Beyond the practitioner/non-practitioner split, differences in scores are not indicative of performance.

Additionally, the MMO terminology used in the MDFE comes from recent literature on studies of behavior in MMOs, which changes over time. While this study used broad and generic terms that have persisted in the domain, with sufficient time it is certain that the common usage of some terms will change and will have to be updated or amended in their definitions. Finally, while this study controlled for participant sex when sampling from our population, the groups differentiated by the MDFE show that this strategy did not sufficiently ensure that the sampling of MMO players was also similarly balanced. Future research should accommodate for this imbalance by having a sample large enough to allow for the groups to be rebalanced after utilizing the MDFE.

8. Conclusion

Research on player behavior in MMOs can benefit from implementing features from research on both expertise and the influence of a community of practice on knowledge and performance. The orthogame/metagame framework includes consideration of both player performance, a component of expertise, and domain specific knowledge, which can describe competence. Assessing proficiencies in *both* the orthogame and metagame can improve our understanding of the psychological processes that influence the sampled player population's behavior in an MMO context. We therefore advocate the use of this orthogame/metagame framework, and consequently measures of player knowledge and behavior in MMOs, as a means of more finely distinguishing between players who are actively engaged in the MMO's community as practitioners from those who are not. By identifying this group of active practitioners within the larger population of potential players, we can determine the most appropriate measures that define their characteristics. This community of practice-driven approach facilitates assessment of the social learning behavior that often occurs in MMOs in a way that an exclusively performance-oriented approach cannot. Expanding the model of MMO expertise to include measures of community-oriented competence will facilitate greater understanding of learning and behavior in MMOs and improve investigations into MMO expertise in future research efforts.

Conflict of interest statement

The authors state that no competing financial interests exist.

References

Alemi, F. (2007). An Avatar's day in court: a proposal for obtaining relief and resolving disputes in virtual world games. *UCLA Journal of Law & Technology, 2007*, 6–6.

Andersen, E., O'Rourke, E., Liu, Y. E., Snider, R., Lowdermilk, J., Truong, D., et al. (2012). The impact of tutorials on games of varying complexity. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 59–68). ACM.

Arsenault, D. (2009). Video game genre, evolution and innovation. *Eludamos. Journal for Computer Game Culture, 3*(2), 149–176.

Ashton, D. (2009). Interactions, delegations, and online digital games players in communities of practice. *Participations: Journal of Audience & Reception Studies, 6*(1).

Baird, D. E., & Fisher, M. (2005). Neomillennial user experience design strategies: utilizing social networking media to support "always on" learning styles. *Journal of Educational Technology Systems, 34*(1), 5–32.

Bartle, R. A. (2004). *Designing virtual worlds*. Indianapolis, IN. Indianapolis, IN: New Riders Publishing.

Bartle, R. A. (2013, June). The decline of MMOs. In *Paper presented at the new directions in the development of creative and media industries international conference, Sha Tin, Hong Kong*. Retrieved from: http://mud.co.uk/richard/The Decline of MMOs.pdf.

Bosser, A. G., & Nakatsu, R. (2006). Hardcore gamers and casual gamers playing online together. In *Entertainment computing (ICEC 2006; pp. 374–377). Lecture notes in computer science*. Berlin Heidelberg: Springer.

Cannon-Bowers, J. A., & Bowers, C. A. (2008). Synthetic learning environments. In J. M. Spector, M. D. Merrill, J. van Merrienboer, & M. P. Driscoll (Eds.), *Handbook of research on educational communications and technology* (3rd ed., pp. 317–327). New York: Lawrence Erlbaum.

Caplan, S., Williams, D., & Yee, N. (2009). Problematic internet use and psychosocial well-being among MMO players. *Computers in Human Behavior, 25*(6), 1312–1319.

Caplar, N., Suznjevic, M., & Matijasevic, M. (2013). Analysis of player's in-game performance vs rating: case study of Heroes of Newerth. In *In 8th international conference on the foundations of digital games*. Retrieved from: http://www.fdg2013.org/program/papers/paper31_caplar_etal.pdf.

Carter, M., Gibbs, M., & Harrop, M. (2012, May). Metagames, paragames and orthogames: a new vocabulary. In *Proceedings of the international conference on the foundations of digital games* (pp. 11–17). ACM.

Castronova, E. (2001). *Virtual worlds: A first-hand account of market and society on the cyberian frontier.* CESifo Working Paper Series No. 618. Retrieved from: http://www.cesifo-group.de/DocDL/cesifo_wp618.pdf.

Chen, V. H. H., Duh, H. B. L., & Ng, C. W. (2009, October). Players who play to make others cry: the influence of anonymity and immersion. In *Proceedings of the international conference on advances in computer entertainment technology* (pp. 341–344). Chicago, IL: ACM.

Chesney, T., Chuah, S. H., Hoffmann, R., Hui, W., & Larner, J. (2014). A study of gamer experience and virtual world behaviour. *Interacting with Computers, 26*(1), 1–11.

Cooke, N. J., Salas, E., & Cannon-Bowers, J. A. (2000). Measuring team knowledge. *Human Factors, 42*(1), 151–173.

Davis, J. P. (2002). *The experience of 'bad' behavior in online social spaces: A survey of online users*. Social Computing Group, Microsoft Research. Retrieved from: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.84.5025&rep=rep1&type=pdf.

Debeauvais, T., Lopes, C. V., Yee, N., & Ducheneaut, N. (2014). Retention and progression: seven months in world of warcraft. In *Proceedings of the 9th international conference on foundations of digital games*.

Debeauvais, T., & Nardi, B. (2010). A qualitative study of Ragnarök Online private servers: in-game sociological issues. In *Proceedings of the fifth international conference on the foundations of digital games (FDG '10)*.

Debeauvais, T., Nardi, B., Schiano, D. J., Ducheneaut, N., & Yee, N. (2011, June). If you build it they might stay: retention mechanisms in World of Warcraft. In *Proceedings of the 6th international conference on foundations of digital games* (pp. 180–187). ACM.

Delalleau, O., Contal, E., Thibodeau-Laufer, E., Ferrari, R. C., Bengio, Y., & Zhang, F. (2012). Beyond skill rating: advanced matchmaking in ghost recon online. *Computational Intelligence and AI in Games, IEEE Transactions on, 4*(3), 167–177.

DeSanctis, G., Fayard, A. L., Roach, M., & Jiang, L. (2003). Learning in online forums. *European Management Journal, 21*(5), 565–577.

Doran, J., & Parberry, I. (2011, June). A prototype quest generator based on a structural analysis of quests from four MMORPGs. In *Proceedings of the 2nd international workshop on procedural content generation in games* (p. 1). ACM.

Ducheneaut, N., Yee, N., Nickell, E., & Moore, R. J. (2006, April). Alone together?: exploring the social dynamics of massively multiplayer online games. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 407–416). ACM.

Eraut, M. (2000). Non-formal learning and tacit knowledge in professional work. *British Journal of Educational Psychology, 70*(1), 113–136.

Ericsson, K. A. (2008). Deliberate practice and acquisition of expert performance: a general overview. *Academic Emergency Medicine, 15*(11), 988–994.

Ericsson, K. A., & Kintsch, W. (1995). Long-term working memory. *Psychological Review, 102*(2), 211.

Galarneau, L. L. (2005). Spontaneous communities of learning: learning ecosystems in massively multiplayer online gaming environments. In *Proceedings of DiGRA 2005 Conference: Changing views – worlds in play. Vancouver, BC*. http://www.digra.org/dl/db/06278.10422.pdf (accessed 19.06.13).

Guthrie, B., Reuter, K., Barkdoll, M., & Hexmoor, H. (2014). *Small team group dynamics in online games. COOS: Scope and theme* (p. 42).

Hadiji, F., Sifa, R., Drachen, A., Thurau, C., Kersting, K., & Bauckhage, C. (2014, August). Predicting player churn in the wild. In *Computational intelligence and games (CIG), 2014 IEEE conference on* (pp. 1–8). IEEE.

Hainey, T., Connolly, T., Stansfield, M., & Boyle, E. (2011). The differences in motivations of online game players and offline game players: a combined analysis of three studies at higher education level. *Computers & Education, 57*(4), 2197–2211.

Hamilton, W. A., Garretson, O., & Kerne, A. (2014, April). Streaming on twitch: fostering participatory communities of play within live mixed media. In *Proceedings of the 32nd annual ACM conference on human factors in computing systems* (pp. 1315–1324). ACM.

Harrison, B., & Roberts, D. L. (2011). Using sequential observations to model and predict player behavior. In *Proceedings of the 6th international conference on foundations of digital games (FDG) Bordeaux, FR*.

Hennig, M. (2013, March). Storytelling, rules and society in Modern MMORPGs. In *In 3rd global conference: Experiential learning in virtual worlds*. Retrieved from: http://www.inter-disciplinary.net/at-the-interface/wp-content/uploads/2013/02/henningexpaper.pdf.

Hoffman, R. (2013, March). An integrated model of macrocognitive work and trust in automation. In *2013 AAAI spring symposium series*.

Hou, A. C., Chern, C. C., Chen, H. G., & Chen, Y. C. (2011). 'Migrating to a new virtual world': exploring MMORPG switching through human migration theory. *Computers in Human Behavior, 27*(5), 1892–1903.

Huffaker, D., Wang, J., Treem, J., Ahmad, M. A., Fullerton, L., Williams, D., et al. (2009, August). The social behaviors of experts in massive multiplayer online role-playing games. In *Computational science and engineering, 2009. CSE'09. International conference on* (Vol. 4, pp. 326–331). IEEE.

Kawale, J., Pal, A., & Srivastava, J. (2009, August). Churn prediction in MMORPGs: a social influence based approach. In *Proceedings of the international conference on computational science and engineering, 2009* (Vol. 4, pp. 423–428). Chicago: IEEE.

Keith, N., & Ericsson, K. A. (2007). A deliberate practice account of typing proficiency in everyday typists. *Journal of Experimental Psychology: Applied, 13*(3), 135.

Kim, B., Park, H., & Baek, Y. (2009). Not just fun, but serious strategies: using metacognitive strategies in game-based learning. *Computers & Education, 52*(4), 800–810.

Klein, G., Moon, B. M., & Hoffman, R. R. (2006). Making sense of sensemaking 1: alternative perspectives. *IEEE Intelligent Systems, 21*(4), 70–73.

Kong, J. S., & Kwok, R. C. (2009). MMOG game-based collaborative learning: an exploratory study and its research potential. In *Pacific Asia conference on information systems (PACIS 2009)* (pp. 90–103).

Law, A. M., & Kelton, D. (2007). *Simulation modeling and analysis* (4th ed.). New York, NY: McGraw-Hill.

Lehdonvirta, V. (2010). Virtual worlds don't exist: questioning the dichotomous approach in MMO studies. *Game Studies, 10*(1). Retrieved from: http://gamestudies.org/1001/articles/lehdonvirta.

Lewis, C., & Wardrip-Fruin, N. (2010, June). Mining game statistics from web services: a World of Warcraft armory case study. In *Proceedings of the fifth international conference on the foundations of digital games* (pp. 100–107). ACM.

Lim, T., & Nardi, B. (2011, June). A study of raiders with disabilities in World of Warcraft. In *Proceedings of the 6th international conference on foundations of digital games* (pp. 161–167). ACM.

Lin, H., & Sun, C. (2005). The "White-Eyed" player culture: grief play and construction of deviance in MMORPGs. In *Digital games research conference 2005, changing views: Worlds in play*. Retrieved from: http://www.digra.org/wp-content/uploads/digital-library/06278.21161.pdf.

Lu, L., Shen, C., & Williams, D. (2014). Friending your way up the ladder: connecting massive multiplayer online game behaviors with offline leadership. *Computers in Human Behavior, 35*, 54–60.

Moura, D., el-Nasr, M. S., & Shaw, C. D. (2011, August). Visualizing and understanding players' behavior in video games: discovering patterns and supporting aggregation and comparison. In *ACM SIGGRAPH 2011 Game Papers* (p. 2). ACM.

Norlin, S. (2013). *Functional shift and semantic change in lord of the rings Online*.

Mälardalen University School of Education, Culture, and Communication. Retrieved from: http://www.diva-portal.org/smash/get/diva2:651376/FULLTEXT01.pdf.
O'Connor, D. L., & Menaker, E. S. (2008). Can massively multiplayer online gaming environments support team training? *Performance Improvement Quarterly, 21*(3), 23–41.
Oppold, P. J., Rupp, M. A., Lakhmani, S. G., & Szalma, J. (2013). *Participant reaction to responses to griefing scenarios* (Unpublished raw data).
Paul, C. A. (2011). Optimizing play: how theorycraft changes gameplay and design. *Game Studies, 11*(2). Retrieved from: http://gamestudies.org/1102/articles/paul.
Pavlas, D. (2010). *A model of flow and play in game-based learning: The impact of game characteristics, player traits, and player states*. Doctoral dissertation. Florida: University of Central Florida Orlando.
Pearce, C. (2008). The truth about baby boomer gamers a study of over-forty computer game players. *Games and Culture, 3*(2), 142–174.
Phillips, J. K., Klein, G., & Sieck, W. R. (2004). Expertise in judgment and decision making: a case for training intuitive decision skills. In D. J. Koehler, & N. Harvey (Eds.), *Blackwell handbook of judgment and decision making* (pp. 297–315).
Prince, S. A., Adamo, K. B., Hamel, M. E., Hardt, J., Gorber, S. C., & Tremblay, M. (2008). A comparison of direct versus self-report measures for assessing physical activity in adults: a systematic review. *International Journal of Behavioral Nutrition and Physical Activity, 5*(1), 56.
Quandt, T., Grueninger, H., & Wimmer, J. (2009). The gray haired gaming generation: findings from an explorative interview study on older computer gamers. *Games and Culture, 4*(1), 27–46.
Reeves, S., Brown, B., & Laurier, E. (2009). Experts at play understanding skilled expertise. *Games and Culture, 4*(3), 205–227.
Reeves, L., & Weisberg, R. W. (1994). The role of content and abstract information in analogical transfer. *Psychological Bulletin, 115*(3), 381–400.
Rosenbaum, P. R. (2005). Heterogeneity and causality: unit heterogeneity and design sensitivity in observational studies. *American Statistician, 59*(2), 147–152.
Schrader, P. G., & McCreery, M. (2008). The acquisition of skill and expertise in massively multiplayer online games. *Educational Technology Research and Development, 56*(5–6), 557–574.
Shim, K. J., Ahmad, M. A., Pathak, N., & Srivastava, J. (2009, August). Inferring player rating from performance data in massively multiplayer online role-playing games (MMORPGs). In *Computational science and engineering, 2009. CSE'09. International conference on* (Vol. 4, pp. 1199–1204). IEEE.
Shim, K. J., Pathak, N., Ahmad, M. A., DeLong, C., Borbora, Z., Mahapatra, A., et al. (2011). Analyzing human behavior from multiplayer online game logs: a knowledge discovery approach. *IEEE Intelligent Systems, 26*(1), 85–89.
Shim, K. J., Sharan, R., & Srivastava, J. (2010). Player performance prediction in massively multiplayer online role-playing games (MMORPGs). *Advances in Knowledge Discovery and Data Mining*, 71–80.
Smith, A. M., Lewis, C., Hullett, K., Smith, G., & Sullivan, A. (2011). *An inclusive taxonomy of player modeling*. University of California. Santa Cruz, Tech. Rep. UCSC-SOE-11–13.
Steinkuehler, C. A. (2004, June). Learning in massively multiplayer online games. In *Proceedings of the 6th international conference on learning sciences* (pp. 521–528). ICLS (International Society of the Learning Sciences).
Steinkuehler, C. A., & Williams, D. (2006). Where everybody knows your (screen) name: online games as "third places". *Journal of Computer-Mediated Communication, 11*(4), 885–909.
Stigliani, I., & Ravasi, D. (2012). Organizing thoughts and connecting brains: material practices and the transition from individual to group-level prospective sensemaking. *Academy of Management Journal, 55*(5), 1232–1259.
Swain, C. (2008). Master metrics 2.0: using metrics-based design techniques to craft better play experiences. In *Paper presented on the game developer conference 2008, San Francisco, CA*.
Taylor, N., de Castell, S., Jenson, J., & Humphrey, M. (2011, August). Modeling play: re-casting expertise in MMOGs. In *Proceedings of the 2011 ACM SIGGRAPH symposium on video games* (pp. 49–53). ACM.
Towne, T. J., Anders Ericsson, K., & Sumner, A. M. (2014). Uncovering mechanisms in video game research: suggestions from the expert-performance approach. *Frontiers in Psychology, 5*, 161. http://dx.doi.org/10.3389/fpsyg.2014.00161.
Tremblay, J., Torres, P. A., Rikovitch, N., & Verbrugge, C. (2013, August). An exploration tool for predicting stealthy behaviour. In *Proceedings of the 2013 AIIDE workshop on artificial intelligence in the game design process* (Vol. 2013)IDP.
van Harmelen, M. (2008). Design trajectories: four experiments in PLE implementation. *Interactive Learning Environments, 16*(1), 35–46.
van Meurs, R. (2007). *How to play the game: A study on MUD player types and their real life personality traits*. Tilburg University: Tilburg University.
Wadley, G., Gibbs, M., & Benda, P. (2007, December). Speaking in character: using voice-over-IP to communicate within MMORPGs. In *Proceedings of the 4th Australasian conference on interactive entertainment* (p. 24). RMIT University.
Wang, J., Huffaker, D. A., Treem, J. W., Fullerton, L., Ahmad, M. A., Williams, D., et al. (2011). Focused on the prize: characteristics of experts in massive multiplayer online games. *First Monday, 16*(8).
Ward, M. (2010). Avatars and sojourners: explaining the acculturation of newcomers to multiplayer online games as cross-cultural adaptations. *Journal of Intercultural Communication, 23*.
Warner, D. E., & Raiter, M. (2005). Social context in massively-multiplayer online games (MMOGs): ethical questions in shared space. *International Review of Information Ethics, 4*.
Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the process of sensemaking. *Organization science, 16*(4), 409–421.
Wenger, E. (2000). Communities of practice and social learning systems. *Organization, 7*(2), 225–246.
Wenger, E. (2006). *Communities of practice: A brief introduction*. Retrieved from http://wenger-trayner.com/wp-content/uploads/2012/01/06-Brief-introduction-to-communities-of-practice.pdf.
Wolf, K. D. (2007). Communities of practice in MMORPGs: an entry point into addiction?. In *Communities and technologies 2007* (pp. 191–208). London: Springer.
Xanthopoulou, D., & Papagiannidis, S. (2012). Play online, work better? examining the spillover of active learning and transformational leadership. *Technological Forecasting and Social Change, 79*(7), 1328–1339.
Xiong, L. (2012). Demographic characteristics, play patterns, and social experiences of Chinese MMO players. *Journal of Virtual Worlds Research, 5*(2).
Yee, N. (2005). Mob. In *The Daedalus project: MMORPG lexicon*. Retrieved from http://www.nickyee.com/daedalus/archives/001313.php.
Yee, N. (2006). The psychology of massively multi-user online role-playing games: motivations, emotional investment, relationships and problematic usage. *Avatars at Work and Play*, 187–207.