# Impact of the Arrangement of Game Information on Recall Performance of Multi-player Online Battle Arena Players

Justin W. Bonny* and

Lisa M. Castaneda

foundry10

This is an uncorrected version of the following published manuscript:

Bonny, J.W. & Castaneda, L.M. (2016). Impact of the arrangement of game information on recall performance of multi-player online battle arena players. *Applied Cognitive Psychology*.

doi: 10.1002/acp.3234

*Corresponding author

Email: justin@foundry10.org; phone: 1-206-686-9780

Acknowledgements:

We would like to thank foundry10 and Valve Corporation staff for their assistance during data collection. The authors are employees of foundry10 which is funded by Gabe Newell who also acts as the CEO of Valve Corporation, maker of Dota 2.

**Abstract**

Individuals who have domain-specific knowledge, such as chess players and dancers, have been found to use schemas to organize and anticipate information. We examined whether multiplayer online battle arena (MOBA) game players use a similar strategy. Participants were presented with a memory task where they recalled the status of game features as displayed on a mini-map. The task contained two conditions: a condition where game features were arranged in a manner consistent with gameplay and a condition where game features were arranged in a random manner. Recall accuracy for highly structured game features was affected by whether a mini-map was consistent or arbitrarily arranged and varied with participants' MOBA expertise. This is in line with previous expertise research that has found that knowledge of underlying probability structures of events contained within schemas is indicative of domain-specific knowledge. This suggests that MOBA players can be used to study skill acquisition.

Keywords: expertise; video game players; memory; multiplayer online battle arena; schemas

**Impact of the Arrangement of Game Information on Recall Performance of Multi-player Online Battle Arena Players**

The rising popularity of professional video gameplay, known as 'eSports', offers a unique opportunity to study the development of expertise. The transition from novice to expert has been studied within a range of competitive games and sports from chess to figure skating (Chase & Simon, 1973; Hodges, Starkes, & MacMahon, 2006). A re-occurring finding is that individuals who are familiar with a sport or game are sensitive to the structure of relevant information as measured by memory recall tasks (Ericsson & Lehmann, 1996). For example, experienced chess players have been found to be more accurate when recalling the positions of chess pieces when they are arranged in a manner that is consistent with common chess move sequences compared to random arrangements (Chase & Ericsson, 1982; Holding & Reynolds, 1982). This sensitivity to rule structure and consistency of game events has been suggested to be indicative of skill acquisition within a domain (Holding & Reynolds, 1982). With the rise of eSports tournaments, an open question is whether eSport players display a similar sensitivity. The complex gameplay mechanics as well as the range of cognitive and social skills required make eSports unique from other knowledge domains and it is unclear as to whether similar effects would be observed with said players. The present study focused on a particular type of eSport genre called multiplayer online battle arenas (MOBAs). We asked MOBA players to memorize and recall game information that was either consistent with or very likely to be observed in a typical match, or randomized information that was inconsistent and had a low probability of being observed in a typical match. In doing so, we sought to address whether players' recall of the game information varied according to whether it was consistent or inconsistent with game mechanics and if MOBA expertise was correlated with the extent of performance differences between these two conditions.

Part of what makes an individual an expert is their ability to recognize and structure information within a particular domain. Classic studies of chess experts provide compelling evidence that masters with years of experience outperform novices when recalling the positions of pieces on boards from real matches compared to randomly placed pieces (Chase & Ericsson, 1982; de Groot, 1965). Higher performance when recalling information consistent with a knowledge domain has been found in other areas of expertise as well (Hodges et al., 2006). For example ballet and modern dancers as well as figure skaters have better performance when recognizing and recalling domain-relevant information that exemplifies typical motor sequences compared to random sequences (Calvo-Merino, Ehrenberg, Leung, & Haggard, 2010; Deakin & Allard, 1991; Starkes, Caicco, Boutilier, & Sevsek, 1990). Differences in consistent versus random sequences have also been observed in neuroimaging data. Using event-related potentials (ERPs), musicians have been found to have a greater negative deflection in the ERP waveform when hearing tones that violated harmonic and pitch regularities (Fujioka, Trainor, Ross, Kakigi, & Pantev, 2004; Koelsch, Schmidt, & Kansok, 2002). This body of research suggests that differences in performance when recalling consistent or regularly structured versus arbitrarily arranged information can be used to characterize whether an individual is familiar with a knowledge domain.

The advantage experts have when recalling information consistent with a knowledge domain is due in part to using schemas to organize information in working memory. For chess, experts have been found to be able to chunk information in working memory more efficiently than novices, greatly condensing information, and allowing more information to be retained (Chase & Simon, 1973). Chunking in turn is enabled by recalling 'templates' or schemas from long-term memory that are used to organize information within working memory according to patterns that an individual has previously encountered (Chase & Ericsson, 1982; Gobet & Simon, 1996). The structure of these schemas are typically defined as a network of nodes representing characteristics or events and connections between nodes representing in part the probability of one characteristic co-occurring with another (Hummel & Holyoak, 2003; McClelland, Mcnaughton, & O'Reilly, 1995; van Kesteren, Ruiter, Fernandez, & Henson, 2012). Theories of skill acquisition suggest that it is the access to these schemas, in addition to learning a large body of domain-specific information, that can distinguish domain experts from novices (Ericsson & Lehmann, 1996). This can be demonstrated when experts and novices are asked to recall information that is relevant to their area of expertise. If a chess expert is presented with a board for which they have a relevant schema they will likely outperform a novice, whereas if that board is novel (e.g., arbitrarily arranged pieces) they have no access to a relevant schema and will likely display no advantage compared to a novice (Holding & Reynolds, 1982). As such, it is predicted that individuals who display a sensitivity to structured information are likely to have expertise within that particular domain.

The expectation of spatial information to be arranged in a predictable layout has also been found to influence how users interact with computer interfaces. For example, it has been found that consistency in the spatial organization of website pages leads to higher performance when a user is visually searching for relevant information (Teevan, 2008). Furthermore, the level of experience that a user has with a particular webpage layout can lead to greater decrements in performance when the organization is changed (Chen, 2000; McCarthy, Sasse, & Riegelsberger, 2003). Similar findings have also been observed in head-up displays (HUDs) in video games. Specifically, experienced gamers are more efficient when using information displayed in HUDs and perceive the spatial layout as more organized compared to novices (Caroux & Isbister, 2016). This provides further evidence that experienced MOBA players are likely to be sensitive to the consistency of the spatial placement of game information.

An open question is whether MOBA players also display an advantage when recalling consistently versus arbitrarily arranged game information given the complexity of game play. Games within this genre are generally highly complicated compared to the genres which have typically been studied when examining the impact of gaming expertise on cognitive skills, specifically first-person shooters (FPS). For example the HUDs of FPS are typically more minimalist than other genres, such as real-time strategy, in that it contains fewer elements of dynamic game information (Caroux & Isbister, 2016). In addition to multiple user interface features, MOBAs typically have more complex gameplay. For example, players select items from many dozens of options in order to enhance the capabilities of their hero, craft hero equipment, and place sentries to extend line of sight. These auxiliary areas are in addition to the primary focus of gameplay, controlling a hero as part of a team within the battle arena.

Similar to other genres, the rules that govern MOBAs tend to vary in the extent to which they limit player action. Specifically, buildings that serve as landmarks throughout the battle arena have a fixed rule in that they must be destroyed in a specific order with outer buildings needing to be destroyed before inner buildings. This limitation of player actions leads to a consistent expectation across game states: if an outer building is intact, inner buildings will also be intact. In contrast, rules for heroes afford mobility in that they can move anywhere within the arena. Although this allows for more variation in gameplay in contrast to buildings, heroes are more likely to be around bases and paths on their team's side of the map compared to the opponents'. As such, players who have greater experience playing a MOBA are likely to expect the location and status of game elements to follow particular patterns. However, given the complexity and variation in the rigidity of game features as described above it is unclear whether individuals who are familiar with MOBAs will display similar effects present in other knowledge domains, such as chess, when recalling information that is consistently or arbitrarily arranged.

In the present study we examined whether MOBA players were sensitive to structured game information. To do so, we used a memory recall task, which, similar to previous research, required participants to recall the spatial placement and status of game information using a minimap. A feature of the HUD, the mini-map provides each player an aerial view of the entire battle arena. A 'fog of war' covers map locations of opponent heroes unless they are within the virtual line of vision of the player's team or buildings. The locations and statuses of all team buildings and teammates are displayed. As such, the mini-map provides the closest analog to chess boards used in previous research (Chase & Simon, 1973; Gobet & Simon, 1998). We developed a recall task where we presented participants with 'real' and 'fake' mini-maps. The real minimaps were taken from actual professional matches and therefore the game states, including building status and hero placement, were consistent with game rules. In contrast, fake minimaps were constructed such that game states violated the rule regarding building destruction and heroes were placed in unlikely positions. Using this task, we examined whether participants would have greater performance in recalling the status and location of buildings and heroes in the real versus fake mini-maps. We predicted that relative performance on the real versus fake mini-maps would vary with MOBA expertise.

# Method

## Study Environment

The study took place at the annual championship tournament for the eSport Dota 2, The International 5 (TI5) at Key Arena in Seattle, WA, USA from August 3rd to August 8th 2015. Data collection for this study took place in a vendor pavilion area located outside the arena.

## Hardware and Software

All components of the study were built using the Python-based OpenSesame experiment builder (v. 2.9.6; Mathôt, Schreij, & Theeuwes, 2012) and custom scripts. Laptops running the Windows 8 operating system were used for the tasks (screen diagonal of 33.78 cm; screen resolution was 1920 x 1080 pixels). Participants used the laptop keyboard and an external wired mouse to complete the tasks.

## Participation Requirements

To participate in the study, individuals had to meet the following requirements. They needed to be fluent in spoken and written English, have knowledge of Dota 2, provide their account login ID for the Steam platform that hosts the game, be attending or staffing the tournament (checked via TI5 badge), and either had to be 18 years of age or older or have parental permission.

## Video Game Description and Experience Measures

The specific MOBA game we selected for this study was the computer game Dota 2 (Valve Corporation, 2015). In this game two teams (team names: “Radiant” and “Dire”) of five players control heroes as they battle within a virtual arena with the goal of destroying the opponent’s base. The game is played online with a centralized server connecting players who are located at various geographic locations. Playing a match proceeds as follows. When joining a match, each player selects a hero that has a unique set of abilities and skills. During the match players use their heroes to destroy their opponents’ heroes, buildings, and computercontrolled soldiers.

The goal of the game is to destroy the opponent base and in the process destroy as many enemy heroes and buildings as possible. Gameplay takes place within a square arena which is roughly divided in half between the two teams with bases located at opposite corners and three paths or ‘lanes’ connecting the two bases. Along these lanes and within each base are buildings that either are defensive (e.g., towers that have ranged attacks) or provide support (e.g., barracks) for each team. On each team’s half of the map there are four sets of towers at different distances from the base aligned along the three lanes and one set of barracks within the base (see Figure 1). Whereas towers attack opponents, barracks provide support for the computer-controlled soldiers. A rule for attacking buildings is that they can only be destroyed sequentially: the outermost (farthest from base) buildings in a lane must be destroyed before buildings closer to the base in that lane can be damaged. At the start of a match, each team has a total of 17 buildings (11 towers, 6 barracks) and five heroes. The majority of the HUD is occupied by a third-person view of the immediate vicinity around the player’s hero as well as a mini-map of the entire battle arena. The mini-map displays the current status and location of all buildings, the location of teammates and friendly computer-controlled soldiers, and the location of enemy heroes and soldiers if they are within a certain distance from a teammate or building.

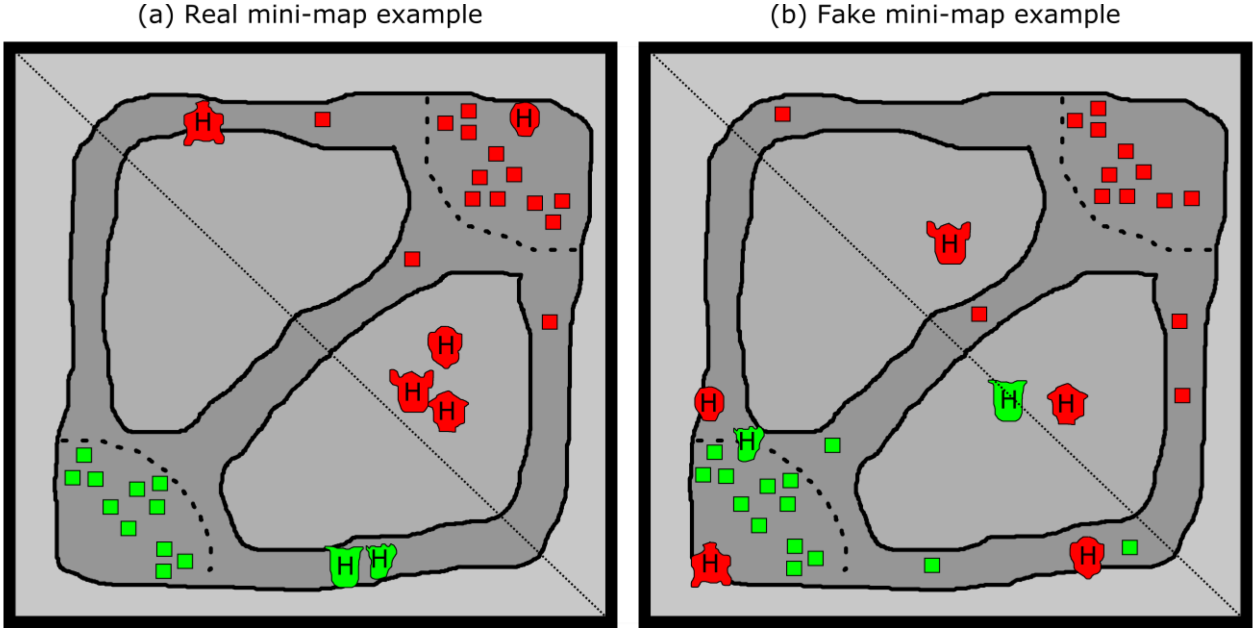


*Figure 1.* Example mini-map snapshots for the Dire team (red icons). The mini-map on the left is a real map, following the rules for the destruction of buildings (indicated by cube icons) and likely placement of heroes (indicated by face icons). The mini-map on the right is a fake map which violates the rules for destroying buildings (inner buildings destroyed before outer buildings) and unlikely placement of heroes (e.g., in opponent's base).

To play Dota 2 individuals need to log into their Steam account and have an active internet connection. By doing so, match statistics are captured and saved to the player's account. Some of these measures are publicly accessible while others are only available to the player and Valve Corporation. We asked for participants' consent to gather their Dota 2 statistics by providing their Steam ID to participate in the study. With the assistance of Valve Corporation we were able to collect objective measures of gamer experience and expertise. Specifically, we included 'total playtime' which indicates the total amount of time a gamer has played Dota 2 (in hours). Additionally, we retrieved matchmaking rankings (MMR). This index of expertise is akin to the Elo rating system of chess players where the higher the ranking indicates a higher skill level player. The MMR rating we selected is generated by the results of unranked matches where players entered the match as part of a team. This was done to maximize the number of participants that could be included in analyses since not every participant had played a ranked or solo match. A player's MMR is used to find an opponent such that there is close to a 50% chance of either player winning a match.

**Mini-map Recall Task**

Participants were asked to memorize the location and status of Dota 2 heroes and buildings as indicated on a mini-map. Participants were presented with two types of snapshots (7.95 cm x 7.62 cm) of Dota 2 mini-maps. Maps in the ‘real’ condition were taken from real matches whereas those in the 'fake' condition were created by randomly arranging features such that the status of buildings and the location of heroes did not make strategic sense or follow rules of the game (e.g., barracks destroyed but not towers; see Figure 1). Across a total of 8 trials we counterbalanced match type (real, fake) and target team (radiant, dire). The order of trials was randomized across participants. Participants were explicitly told that they would be viewing real and fake mini-maps.

Prior to the presentation of mini-map snapshots, participants were presented with the team name (“radiant”, “dire”) for 800 ms to indicate which they were to memorize. Then the snapshot of the match mini-map was presented for 5 seconds, in-line with previous chess expertise research (Chase & Simon, 1973) and immediately afterwards a blank mini-map was presented. Participants then completed three rounds of information recall regarding player and building statuses. First they indicated the status of the team buildings by clicking either a 'destroyed' (building was not present on mini-map) or 'alive' (building was on mini-map) button with the mouse cursor. The software automatically highlighted the building for which the decision was to be made in a fixed sequence across all 17 buildings. Next, they indicated the position of the team heroes that were alive by clicking a location on the map and heroes that were destroyed by clicking within a 'destroyed' box located below the mini-map. These judgments only indicated where the five heroes were located using a placeholder icon, not the specific identities of heroes. Finally, they were presented with hero icons individually and clicked the placeholder icon that corresponded to the position they believed the hero was located (selecting from the mini-map or 'destroyed' box). Participants were asked to respond as quickly as possible, but there was no time limit. The dependent variables were proportion of correctly identified building and hero statuses (buildings and heroes that were correctly identified as being alive or destroyed), the median reaction time (RT) for judging building and hero statuses (placing hero icons on placeholders within the mini-map or destroyed box), and the average distance between placed locations and true locations for heroes that were correctly identified as alive (distance measured in pixels). All analyses were conducted using R statistical software (v 3.2.0).[1]

### Study Procedure

Upon agreeing to take part in the study, participants were presented with an electronic consent form that abided by the guidelines of the Declaration of Helsinki. They were explicitly told that in addition to the data collected using the computerized tasks that their Dota 2 play statistics would be retrieved using their Steam ID and provided written consent for doing so. They were then asked to read the instructions for the task carefully. Next, they completed the recall task and afterwards provided demographic information. Upon completion they were presented with an electronic debriefing and with an incentive (t-shirt or plush doll). The entire study took approximately 20 to 30 minutes to complete.

## Results

### Participants

A total of 208 participants completed the study. Of these participants, 24 were dropped due to not having an MMR rating and 13 were identified as outliers by having median response times beyond 3**SD* of the mean for building or hero status judgments. In the final dataset, a total of 14 females, 155 males, and 2 individuals who identified their gender as “other” were retained (*N* = 171) and average age was 23.49 years (*SD* = 3.6, *Min* = 15, *Max* = 40). Of the participants, 155 provided valid education information with 11 completing at least some graduate schooling, 111 completing at least some college, 29 completing at least some high school, and 4 completing at least some middle school. Participants were from a range of ethnic and racial backgrounds with 13 identifying as Hispanic, 3 as American Indian, 1 as Pacific Islander, 96 as Caucasian, 51 as Asian, and 17 as multiple races.

## Performance on Real versus Fake Maps and MOBA Expertise

**Measure of MOBA Expertise.** Using player statistics from Dota 2 we combined two measures into a single expertise score using factor analysis. The two measures we selected were total hours playing Dota 2 (*M* = 2196.75, *SD* = 1731.08, *Min* = 0.00, *Max* = 9616.32) and MMR from unranked team matches (*M* = 3226.26, *SD* = 1111.46, *Min* = 0.00, *Max* = 5237.00). We took this approach since, although not traditional measures of expertise such as deliberate practice (Ericsson & Lehmann, 1996), both measures are indicators of expertise and by combining both measures we aimed to create a more accurate estimate of expertise (Macnamara, Hambrick, & Oswald, 2014). We used the 'fa' function from the '*psych*' r-package using the '*minres*' method, to derive an expertise score (1-factor solution: eigenvalue = 1.1, Tucker Lewis Index of factoring reliability = 1.0; see Figure 2).[2]

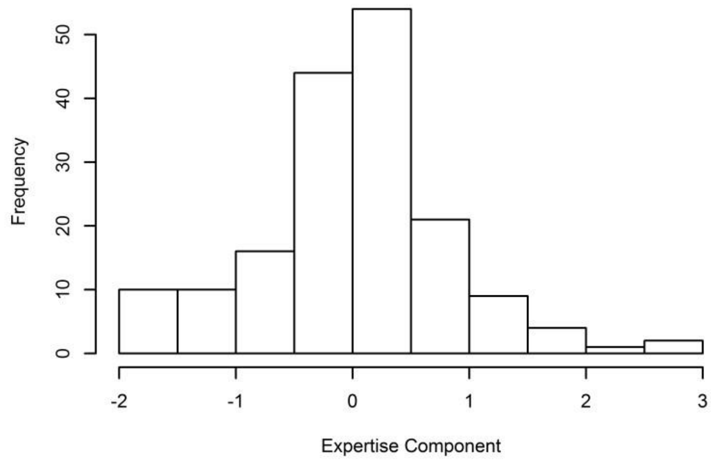


***Figure 2.*** Histogram of MOBA expertise scores calculated using factor analysis.

**Predicting recall performance.** We next examined whether performance varied by type of mini-map and whether this effect was mediated by MOBA expertise (see Table 1 for descriptive statistics). To do so, we ran linear mixed-model analyses to predict each dependent variable with map type (coding: fake = 0, real = 1) and MOBA expertise as factors using the maximum likelihood method (see Table 2 for results).[3] We present the estimated variance accounted for by each model using the $\Omega_0^2$ statistic (Xu, 2003). We observed a significant effect of map type for building score (null model: AIC = 965.53, $\Omega_0^2 < 0.001$; overall model: AIC = 466.68, $X^2[3] = 514.88$, $p < 0.001$, $\Omega_0^2 = 0.811$), hero score (null model: AIC =975.22, $\Omega_0^2 = 0$; overall model: AIC = 927.14, $X^2[3] = 54.41$, $p < 0.001$, $\Omega_0^2 = 0.147$), hero RT (null model: AIC = 963.40, $\Omega_0^2 = 0.415$; overall model: AIC = 952.51, $X^2[3] = 39.90$, $p < 0.001$, $\Omega_0^2 = 0.572$), and hero mean distance (null model: AIC = 975.55, $\Omega_0^2 = 0$; overall model: AIC = 440.95, $X^2[3] = 540.6$, $p < 0.001$, $\Omega_0^2 = 0.815$). A significant interaction between expertise and map type limited to building score was driven by a significant correlation between expertise and building score specific to the real mini-map condition, $r(169) = 0.180$, $p = 0.019$ (fake condition, $r = -0.071$, $p = 0.356$). No significant effects were observed for building RT (null model: AIC = 965.53, $\Omega_0^2 = 0.385$; overall model: AIC = 970.98, $X^2[3] = 0.546$, $p = 0.909$, $\Omega_0^2 = 0.388$). These results suggest that experienced players were more likely to accurately recall the status of buildings in the real mini-map condition compared to less experienced players (see Figure 3).

**Table 1**

*Descriptive statistics for mini-map recall performance by map type (real, fake).*

| Variable | Condition | *M* | *SD* | *Min* | *Max* |
|---|---|---|---|---|---|
| Building Accuracy | Real | 0.88 | 0.06 | 0.62 | 0.99 |
| | Fake | 0.65 | 0.06 | 0.43 | 0.82 |
| Hero Accuracy | Real | 0.78 | 0.06 | 0.65 | 0.95 |
| | Fake | 0.84 | 0.07 | 0.50 | 0.90 |
| Building RT (ms) | Real | 673.48 | 174.71 | 401.15 | 1338.26 |

| | | | | | |
|---|---|---|---|---|---|
| | Fake | 660.48 | 201.05 | 295.03 | 1336.32 |
| Hero RT (ms) | Real | 1150.14 | 418.10 | 273.00 | 2448.50 |
| | Fake | 1422.26 | 529.47 | 256.50 | 3209.50 |
| Hero Mean Distance (pixels) | Real | 130.97 | 26.89 | 65.74 | 203.20 |
| | Fake | 233.08 | 25.33 | 169.99 | 307.20 |

**Table 2**

*Estimated fixed effect coefficients for linear mixed-models predicting recall performance (SE = standard error).*

| Dependent Variable | Factor | Estimate (SE) | t-value | p-value |
|---|---|---|---|---|
| Building Score | | | | |
| | Intercept | -0.878 (0.036) | -24.367 | $<0.001^{***}$ |
| | Expertise | -0.034 (0.036) | -0.946 | 0.344 |
| | Map Type | 1.756 (0.049) | 35.973 | <0.001[1] |
| | Expertise x Map Type | 0.119 (0.049) | 2.430 | $0.015^{*}$ |
| Hero Score | | | | |
| | Intercept | 0.376 (0.071) | 5.327 | $<0.001^{***}$ |
| | Expertise | -0.081 (0.071) | -1.143 | 0.253 |
| | Map Type | -0.751 (0.1) | -7.534 | $<0.001^{***}$ |
| | Expertise x Map Type | 0.013 (0.1) | 0.133 | 0.894 |
| Building RT | | | | |
| | Intercept | -0.035 (0.076) | -0.453 | 0.651 |
| | Expertise | -0.005 (0.076) | -0.066 | 0.947 |
| | Map Type | 0.069 (0.094) | 0.734 | 0.463 |
| | Expertise x Map Type | 0.008 (0.094) | 0.083 | 0.934 |
| Hero RT | | | | |
| | Intercept | 0.275 (0.073) | 3.743 | $<0.001^{***}$ |
| | Expertise | -0.039 (0.073) | -0.537 | 0.591 |
| | Map Type | -0.549 (0.083) | -6.652 | $<0.001^{***}$ |
| | Expertise x Map Type | 0.068 (0.083) | 0.818 | 0.414 |
| Hero Mean Distance | | | | |
| | Intercept | 0.89 (0.035) | 25.658 | $<0.001^{***}$ |
| | Expertise | -0.004 (0.035) | -0.122 | 0.903 |
| | Map Type | -1.779 (0.048) | -37.308 | $<0.001^{***}$ |
| | Expertise x Map Type | -0.02 (0.048) | -0.420 | 0.674 |

[1] $p < .001$, $^{*}p < .05$

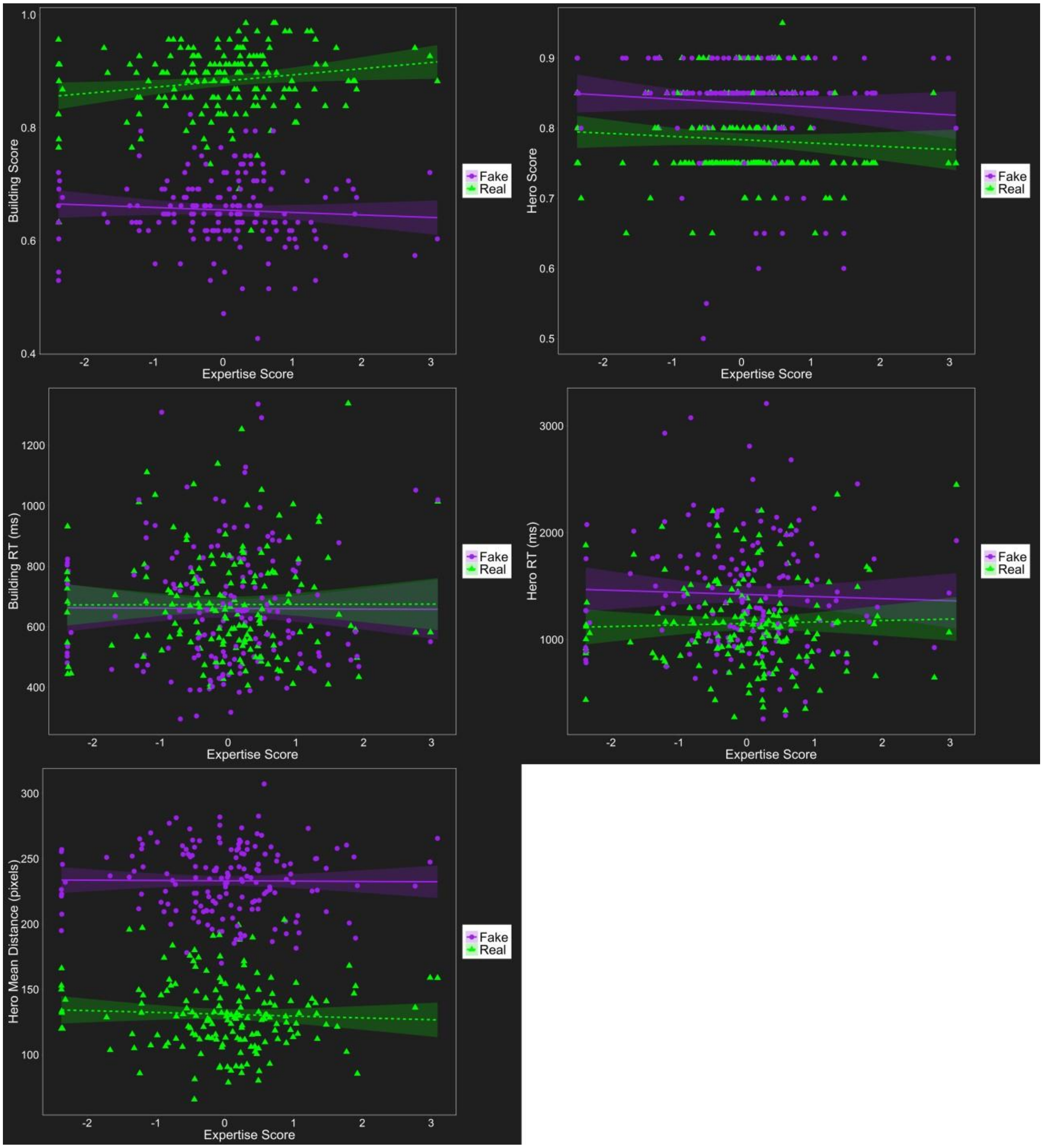


***Figure 3.*** Scatter plots of participant performance for each dependent variable for real and fake mini-map conditions. Lines of best fit are plotted for each mini-map condition with estimated 95% confidence interval indicated by shading.

Next we examined which dependent variables could most differentiate between whether a participant was viewing a fake or real map. To do so, we ran a mixed-model binary logistic regression predicting whether a map was real or fake (coding: real = 1, fake = 0) using building status accuracy, hero status accuracy, building status RT, hero status RT, and hero mean distance as predictors.[3] The overall model was a significantly better fit compared to a null model (null model: AIC = 478.11, $\Omega_0^2$ = 0; overall model: AIC = 25.84, $X^2[7]$ = 462.276, $p$ < 0.001, $\Omega_0^2$ = 0.862). Of the dependent variables, we observed that building accuracy was a significant predictor, while hero mean distance was a marginal predictor (see Table 3).

**Table 3**

*Binary logistic regression using mini map recall performance to predict whether a map was real or fake.*

| | **Fixed Effects Coefficient** | **Std. Error** | **z-value** | ***p*** |
|---|---|---|---|---|
| (Intercept) | 2.037 | 1.597 | 1.275 | 0.202 |
| Building Accuracy | 4.142 | 1.798 | 2.304 | 0.021* |
| Hero Accuracy | 0.040 | 0.744 | 0.054 | 0.957 |
| Building RT | -0.191 | 0.889 | -0.214 | 0.830 |
| Hero RT | -2.135 | 1.594 | -1.340 | 0.180 |
| Hero Mean Distance | -12.888 | 7.651 | -1.684 | 0.092 |

## Discussion

Consistent with previous research in other domains, we found that MOBA players were sensitive to the consistency of mini-map information with regard to the underlying game structure when presented with a recall task. Accuracy was higher when recalling the status of buildings, reaction times were faster when recalling the status of heroes, and the recalled locations of heroes were more precise in the real mini-map condition. When comparing the discriminatory value of all performance measures when predicting whether a mini-map was real or fake, building status was the only significant predictor. In addition to these results we observed an interaction between MOBA player expertise and mini-map type for building status accuracy: participants who had higher expertise were more accurate when recalling building status on the real mini-map condition. These results support our hypotheses that MOBA players are sensitive to the degree to which map information was consistent with the game structure and that expert MOBA players were sensitive to a greater extent that novice players.

The present study demonstrates that MOBA expertise can affect the recall of relevant information. To our knowledge, this is the first study that has examined the performance of MOBA players on a recall task that varied the consistency of mini-map features with game rules and likely events. This is in line with previous expertise research that has examined the impact of game information consistency with athletes and chess players (Calvo-Merino et al., 2010; Chase & Simon, 1973; Deakin & Allard, 1991; Starkes et al., 1990). In the present study, the finding that performance was generally higher for the real versus fake mini-maps parallels what has been observed in chess expertise studies; experts have better recall when presented with stimuli that have plausible compared to random arrangement of game features (Gobet & Simon, 1996). Additionally, our results are in line with human computer interaction research investigating the development of schemas in relation to software websites. Specifically, experience with the spatial layout of an interface is argued to be incorporated into a schema and changes in these layouts can lead to decrements in performance when navigating these interfaces (Chalmers, 2003; Chen, 2000; McCarthy et al., 2003; Teevan, 2008). Across these subject areas, expertise within a knowledge domain can be represented in part as an individual's awareness of conditional rules and probabilities of events (Abernethy, Gill, Parks, & Packer, 2001). In line with statistical learning (Durrant, Cairney, & Lewis, 2011; van Kesteren et al., 2012) it is likely that MOBA players implicitly encode and store the frequency and patterns of game events in long-term memory and rely on these schemas to predict and organize real-time game information. A novel finding in the present study was that differences in how strongly specific features within the mini-map game states conflicted with game rules were reflected in the predictive value of building and hero measures: whereas building accuracy significantly predicted map-type, hero status did not. In other words, the rigidity of the building destruction rule compared to the more flexible placement of heroes in the arena was reflected in the predictive strength of the corresponding measures. That this finding was present even though participants were explicitly told that fake mini-maps would be displayed provides strong evidence that participants were sensitive to the degree to which a game feature violated their expectations.

If the probability structure of events contributed to performance differences when recalling game features, it may seem puzzling as to why participants more accurately judged building status with real mini-maps and hero status for fake mini-maps. We believe part of the reason may be that in a MOBA, like Dota 2, there is a chance that a hero can appear in any location within the arena unlike buildings and structures. In the fake condition, participants could have quickly recognized that the status of buildings was not plausible shifted their attention to focus on the hero placement since this did not violate their expectations of the game. Evidence suggesting greater attention being devoted to recalling hero information at the expense of building status is higher accuracy for hero versus building status judgments in the fake condition and the longer reaction times of players when indicating heroes were alive or destroyed for the fake versus real mini-maps (see Table 1).

That building status accuracy predicted participant MOBA expertise further suggests that participants were relying on previous experience to anticipate the status of game features. During a match, players are distributing attention to multiple facets of gameplay. Players must manage micro-transactions to obtain items to enhance their hero, communicate with teammates to coordinate their actions, and select the attacks and spells of their hero. This is all considered while contemplating the movements and actions of the opposing team which are sporadically and partially visible due to limited virtual line of vision. As such, players must often anticipate when an enemy hero may attack their team based on the status and location of friendly heroes and buildings. In the midst of such a dynamic and complex environment it is likely that players experience a high level of cognitive load (Beckmann, 2010). As such, MOBA players likely recruit schemas to efficiently encode and organize information. Reliance on structures in longterm memory, such as schemas, have been found to increase during high cognitive load (Sherman, Lee, Bessenoff, & Frost, 1998). That in the present study hero and building status accuracy was above chance suggests that MOBA players relied in large part on schemas they developed with experience. This seems especially likely considering there were a total of 22 decisions per trial and stimuli were presented for five seconds. This is supported by the significant relation between building status accuracy and MOBA expertise and is in line with previous research with chess experts (Chase & Simon, 1973; Gobet & Simon, 1996). Given the complexity and dynamic nature of gameplay it is possible that MOBA players are even more susceptible to having low performance with incompatible or arbitrarily arranged game information compared to other areas of expertise. Future research that compares participants that are naïve to MOBA games to MOBA experts can examine whether the complexity of the game genre leads to a greater decrement in performance with randomly arranged mini-maps compared to other areas of expertise (e.g., chess).

**Footnotes**

[1] Team, R. C. (2015). R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria. Retrieved from http://www.r-project.org/

[2] Revelle, W. (2015). psych: Procedures for Personality and Psychological Research. Evanston, Illinois, USA: Northwestern University. Retrieved from http://cran.r-project.org/package=psych

[3] Bates, D., Maechler, M., Bolker, B., & Walker, S. (2014). lme4: Linear mixed-effects models using Eigen and S4. Retrieved from http://cran.r-project.org/package=lme4

**References**

Abernethy, B., Gill, D. P., Parks, S. L., & Packer, S. T. (2001). Expertise and the perception of kinematic and situational probability information. *Perception*, *30*, 233–252. http://doi.org/10.1068/p2872

Beckmann, J. F. (2010). Taming a beast of burden - On some issues with the conceptualisation and operationalisation of cognitive load. *Learning and Instruction*, *20*(3), 250–264. http://doi.org/10.1016/j.learninstruc.2009.02.024

Calvo-Merino, B., Ehrenberg, S., Leung, D., & Haggard, P. (2010). Experts see it all: Configural effects in action observation. *Psychological Research*, *74*(4), 400–406. http://doi.org/10.1007/s00426-009-0262-y

Caroux, L., & Isbister, K. (2016). Influence of head-up displays' characteristics on user experience in video games. *International Journal of Human-Computer Studies*, *87*, 65–79. http://doi.org/10.1016/j.ijhcs.2015.11.001

Chalmers, P. A. (2003). The role of cognitive theory in human–computer interface. *Computers in Human Behavior*, *19*(5), 593–607. http://doi.org/10.1016/S0747-5632(02)00086-9

Chase, W. G., & Ericsson, K. A. (1982). Skill and working memory. *The Psychology of Learning and Motivation*, *1*(1), 1 – 51. http://doi.org/10.1016/S0079-7421(08)60546-0

Chase, W. G., & Simon, H. A. (1973). Perception in chess. *Cognitive Psychology*, *4*(1), 55–81. http://doi.org/10.1016/0010-0285(73)90004-2

Chen, C. (2000). Individual differences in a spatial-semantic virtual environment. *Journal of the American Society for Information Science*, *51*(1994), 529–542. http://doi.org/10.1002/(sici)1097-4571(2000)51:6<529::aid-asi5>3.0.co;2-f de Groot, A.

(1965). *Thought and choice in chess*. *The American Journal of Psychology* (Vol. 79). http://doi.org/10.5117/9789053569986

Deakin, J. M., & Allard, F. (1991). Skilled memory in expert figure skaters. *Memory & Cognition*, *19*(1), 79–86. http://doi.org/10.3758/BF03198498

Dota2. (2015). Bellevue, WA: Valve Corporation.

Durrant, S. J., Cairney, S., & Lewis, P. A. (2011). Sleep-dependent consolidation of statistical learning. *Neuropsychologia*, *49*, 1322–1331. http://doi.org/10.1016/j.neuropsychologia.2011.02.015

Ericsson, K. A., & Lehmann, A. C. (1996). Expert and exceptional performance: evidence of maximal adaptation to task constraints. *Annual Review of Psychology*, *47*, 273–305. http://doi.org/10.1146/annurev.psych.47.1.273

Fujioka, T., Trainor, L. J., Ross, B., Kakigi, R., & Pantev, C. (2004). Musical training enhances automatic encoding of melodic contour and interval structure. *Journal of Cognitive Neuroscience*, *16*(6), 1010–21. http://doi.org/10.1162/0898929041502706

Gobet, F., & Simon, H. A. (1996). Templates in chess memory: a mechanism for recalling several boards. *Cognitive Psychology*, *31*(1), 1–40. http://doi.org/10.1006/cogp.1996.0011

Gobet, F., & Simon, H. A. (1998). Expert chess memory: revisiting the chunking hypothesis. *Memory (Hove, England)*, *6*(3), 225–255. http://doi.org/10.1080/741942359

Hodges, N. J., Starkes, J. L., & MacMahon, C. (2006). Expert performance in sport: A cognitive perspective. *The Cambridge Handbook of Expertise and Expert Performance.*

Holding, D. H., & Reynolds, R. I. (1982). Recall or evaluation of chess positions as determinants of chess skill. *Memory & Cognition*, *10*(3), 237–242. http://doi.org/10.3758/BF03197635

Hummel, J. E., & Holyoak, K. J. (2003). A symbolic-connectionist theory of relational inference and generalization. *Psychological Review*, *110*(2), 220–264. http://doi.org/10.1037/0033-295X.110.2.220

Koelsch, S., Schmidt, B.-H., & Kansok, J. (2002). Effects of musical expertise on the early right anterior negativity: an event-related brain potential study. *Psychophysiology*, *39*(5), 657–663. http://doi.org/10.1017.S0048577202010508

Macnamara, B. N., Hambrick, D. Z., & Oswald, F. L. (2014). Deliberate practice and performance in music, games, sports, education, and professions: a meta-analysis. *Psychological Science*, *25*(8), 1608–18. http://doi.org/10.1177/0956797614535810

Mathôt, S., Schreij, D., & Theeuwes, J. (2012). OpenSesame: An open-source, graphical experiment builder for the social sciences. *Behavior Research Methods*. http://doi.org/10.3758/s13428-011-0168-7

McCarthy, J. D., Sasse, A. M., & Riegelsberger, J. (2003). Could I have the menu please? An eye tracking study of design conventions. In *Proceedings of HCI2003* (pp. 401–414).

McClelland, J. L., Mcnaughton, B. L., & O'Reilly, R. C. (1995). Why there are complementary learning systems in the hippocampus and neocortex : Insights from the successes and failures of connectionist models of learning and memory. *Psychological Review*, *102*(3), 419–457. http://doi.org/10.1037/0033-295X.102.3.419

Sherman, J. W., Lee, A. Y., Bessenoff, G. R., & Frost, L. A. (1998). Stereotype efficiency reconsidered: Encoding flexibility under cognitive load. *Journal of Personality and Social Psychology*, *75*(3), 589–606. http://doi.org/10.1037/0022-3514.75.3.589

Starkes, J., Caicco, M., Boutilier, C., & Sevsek, B. (1990). Motor recall of experts for structured and unstructured sequences in creative modern dance. *Journal of Sport & Exercise Psychology*, *12*(3), 317–321.

Teevan, J. (2008). How people recall, recognize, and reuse search results. *ACM Transactions on Information Systems*, *26*(4), 1–27. http://doi.org/10.1145/1402256.1402258 van Kesteren, M. T., Ruiter, D. J., Fernandez, G., & Henson, R. N. (2012). How schema and novelty augment memory formation. *Trends in Neurosciences*, *35*(4), 211–219. http://doi.org/10.1016/j.tins.2012.02.001

Xu, R. (2003). Measuring explained variation in linear mixed effects models. *Statistics in Medicine*, *22*(22), 3527–3541. http://doi.org/10.1002/sim.1572