Sport, Exercise, and Performance Psychology
2016, Vol. 5, No. 4, 308–323

2157-3905/16/$12.00 http://dx.doi.org/10.1037/spy0000070

Dynamic Effects on Elite and Amateur Performance

William C. Woods, Daniel J. Hayes, Francisco Meyer, Omid Kardan, and Marc G. Berman
The University of Chicago

Sport psychology research has focused on interpersonal differences to predict performance. However, a growing literature has demonstrated the influence of intrapersonal shifts in psychological processes on performance outcomes. Although investigations have examined intrapersonal variation in psychological processes, there has been little exploration into variation in the behaviors that comprise athletic performance itself. Understanding the extent to which performance behaviors change as a function of opponent and time is critical to understanding how fluctuations in psychological processes may influence performance. Three studies examined the influence of dynamic, within-person variation on athletic performance. In Study 1, we detected dynamic effects on tennis players' serving speed. In Study 2, we showed similar dynamic effects in user inputs by elite e-sport players. In Study 3, we replicated the dynamic effects on performance in a sample of amateur e-sport players. Findings provided preliminary evidence that dynamic variability in performance represents a significant proportion of variance.

Keywords: within-person variation, dynamic process, performance process, sport, variance partitioning

Measurement of athletic performance is an area of special interest within sports psychology. Many investigations have explored the extent to which trait-like, between-person differences predict divergent performance outcomes (Gaudreau, Nicholls, & Levy, 2010). These studies typically examine how individuals with one characteristic differ from individuals with another characteristic. For example, an investigator may be interested in performance differences between men and women, or between athletes with high anxiety and low anxiety. Trait-level research typically obtains only one measurement for each individual and is unable to account for variations in individual affect, thought, and action over time and across situations (Shavelson & Webb, 1991). There is, however, a growing body of recent research that has utilized dynamic, within-person study designs to explore how change over time and situation is related to performance outcome in sport. To date, however, these within-person investigations of dynamic effects have focused on the extent to which variations in psychological processes predict performance outcome. Understanding the extent to which athletic performance itself is malleable across time and opponents may provide insight into the how intrapersonal shifts in psychological processes affect performance outcome in sport.

Trait-level research in sports psychology has been successful in identifying intrapersonal, interpersonal, and situational characteristics that predict superior athletic performance. For example, investigations have described how testosterone (Aguilar, Jiménez, & Alvero-Crus, 2013) and cortisol (Filaire, Alix, Ferrand, & Verger, 2009) levels change before and after intense competition. Beyond physiology, athletes with strong feelings of precompetition vigor are likely to have superior performance compared with those with less vigor (Beedie, Terry, & Lane, 2000). Situational effects on

This article was published Online First July 21, 2016.

William C. Woods, Daniel J. Hayes, Francisco Meyer, Omid Kardan, and Marc G. Berman, Department of Psychology, The University of Chicago.

The authors thank Brian Lakey for methodological assistance.

Correspondence concerning this article should be addressed to William C. Woods or Marc G. Berman, Department of Psychology, University of Chicago, 416 Green Hall, Chicago, IL 60637. E-mail: willcwoods@gmail.com or bermanm@uchicago.edu

performance have also been documented such as the lower anxiety levels of team-sport athletes relative to those in individual sports (Martens, Burton, Vealey, Bump, & Smith, 1990).

Although trait-level research has documented intrapersonal, interpersonal, and situational effects on performance, there are conflicting findings that highlight the limitations of between-person research. For example, anxiety may be beneficial to some athletes, but deleterious to others (Hanin, 1997). Similarly, Anshel and Wells (2000) showed that the overall use of coping is not as effective a predictor of performance outcomes as the specific type of coping strategy deployed. These inconsistencies suggest that the influence of typically characterized traits may be more situationally dependent than previously theorized. If some athletes thrive at higher levels of anxiety, while others do not, comparisons of the effect of relative levels of anxiety will not be meaningful. In order for trait-like differences to be robust, relative levels of a characteristic need to have similar effects across individuals (i.e., main effect).

When a characteristic's effect is not consistent across individuals, it may be beneficial to examine how different levels of that characteristic afect the same individuals over time, for example, how shifts in an athlete's anxiety are linked to changes in outcome performance. This style of research typically utilizes within-person designs to detect dynamic processes in affect, thought, and action.

Recently, within-person research designs have been deployed to understand how changes in an athlete's psychological processes can affect performance. One of the most cited models is the individual zones of optimal functioning (IZOF; Hanin, 1997). IZOF combines dynamic and trait-level research to understand how positive and negative emotions influence performance. In applied settings, sport psychologists develop an athlete's unique profile of optimal emotion using positivity–negativity and optimality–dysfunctionality dimensions. For example, moderate anxiety may be negative and optimal for one athlete, but negative and dysfunctional for another. Thus, the closer an athlete is to being "in the zone" of optimal emotion, the better his or her performance. This effect has been extensively documented with a meta-analysis of over 6,000 athletes, finding that those who were "in the zone" performed at one half a standard deviation unit better than those who were not (Jokela & Hanin, 1999). More recently, Hagtvet and Hanin (2007) examined the consistency of athlete emotion profiles across strong and poor performances and reported a consistent profile for successful performances but no pattern within unsuccessful performances.

Similarly, a study of elite youth soccer players reported low interplayer agreement on the supportiveness of coaches (Rees, Freeman, Bell, & Bunney, 2012). Across three studies, the authors reported that idiosyncratic personal taste explained more of the variance in judgments of coaches' supportiveness than did a trait-like tendency of athletes to see coaches as more or less supportive. Furthermore, these idiosyncratic perceptions of supportiveness extend beyond an athlete's tendency to view all coaches as supportive. A recent replication by Coussens, Rees, and Freeman (2015) reported similarly strong dynamic variability in supportiveness judgments across two studies. Athletes showed little agreement as to which coaches were supportive or agreeable. Most of the variation was accounted for by idiosyncratic relationships (i.e., relational influences) between athletes and coaches. Furthermore, the relational aspects of support were correlated with hypothesized antecedents of perceived support. Athletes who viewed a coach as unusually agreeable and competent also tended to view that same coach as unusually supportive. These studies provide evidence that psychological processes in sport are subject to dynamic process variance.

In addition, studies of dynamic shifts in psychological processes have been linked to performance outcome. Gaudreau, Nicholls, and Levy (2010) explored the extent to which dynamic variation in coping predicted performance outcomes in golfers. When controlling for trait-level differences in athletic ability, dynamic variation in the coping utilized by the athletes strongly predicted subjective judgments of performance and moderately predicted objective performance outcomes. In a similar study, Doron and Gaudreau (2014) investigated the extent to which prior performance affected psychological processes, and whether these in turn predicted later outcomes, in elite fencers in a simulated competition. Previous performance outcomes were predictive of shifts in the psy-

chological processes of the athletes, but the psychological processes were not predictive of later outcomes. These studies reflect recent successes in applying within-person research designs to detect dynamic effects on sports performance.

These dynamic effects investigations are, however, somewhat limited. Although shifts in cognitive processes such as affect and coping were tracked within each athlete, similar variation in athletic process behaviors was not measured. It would be useful, for example, to know the extent to which a professional tennis player's serving speed varies over time and opponent. Understanding shifts in process performance behaviors would allow researchers to differentiate shifts in outcome due to dynamic psychological processes from shifts due to variation in performance. To date, however, dynamic variation in process-related performance behavior has not been explored systematically. Therefore, the aim of the current investigation was to identify the extent to which process-related athletic behaviors vary across opponents and over time. Study 1 assessed the variation in a single process-related behavior in elite tennis players at an international event. Study 2 explored variation in all possible process-related behaviors in world-class e-sport players in a global tournament. Finally, in order to test whether our findings generalize beyond elite performers, Study 3 features a sample of amateur e-sport players.

General Methodological Considerations

Measurement of dynamic, within-person variation of behavior is different from investigations focused on trait-like, between-person differences, because dynamic effects research focuses on what trait-level research conceptualizes as measurement error (Shavelson & Webb, 1991). Trait-level research divides participants into groups based upon different levels of a common characteristic, such as anxiety level. In this design, differences within groups are essentially error; ideally, group members would share identical levels of anxiety in order to more precisely examine the role of high or low anxiety in predicting outcome. In dynamic process designs, each participant is treated as her own group of observations, and shifts in a given characteristic across situations are the focus of the investigation. In other words, dynamic process designs are interested in how an individual is different from herself in a given characteristic at one observation relative to another observation.

The current investigation used the framework of the Social Relations Model (SRM; Kenny, 1994; Kenny, Kashy, & Cook, 2006) to differentiate stable, between-person and dynamic, within-person influences on athletic performance. Trait-like effects can be conceptualized as the difference in mean scores on a performance variable between athlete **A** and athlete **B**, for example, the tendency of athlete **A** to always perform better than athlete **B**. These influences will henceforth be referred to as athlete effects.[1]

Dynamic variance can come from two sources: opponents and time. The social sources are measured as Opponent effects and Athlete × Opponent interactions. Opponent effects reflect the extent to which a given opponent tends to elicit the same change in performance by all athletes.[2] Athlete × Opponent interactions reflect idiosyncratic differences in performance in particular athlete–opponent pairs (i.e., relational influences). For example, whereas opponent **E** may elicit a strong change in process behaviors in athlete **A**, the same opponent may not elicit any shift in athlete **B**. When athletes do not share the same opponents, Opponent effects and Athlete × Opponent interactions are confounded into a single effect (i.e., competition effect). Thus, competition effects reflect the extent to which some opponents elicit greater (or worse) performance than others.

In addition to the influence of opponents on variation in process performance, we were also interested in changes in process behavior over time. In tennis, a set is composed of up to 12 games, and is won when one player wins 6 games with a 2-game advantage. (Note: If players are tied at 6 games all, the set is decided by a tiebreaker.) In electronic sport, the terms "set" and "game" both refer to a single game session. In both professional tennis and e-sport, a match consists of several sets, and is usually won on a "best of" basis (e.g., best of three sets). Addi-

[1] Athlete effects are identical to perceiver effects in the SRM.

[2] Opponent effects are identical to target effects in the SRM.

tionally, because sets are crossed with athletes, we are able to measure the main effect of set on all athletes and the Athlete × Set interactions, which are the extent to which particular sets influence the performance of particular athletes. For example, an interaction would occur if the third set in a match always brought out stronger performance in athlete **A**, but did not affect the performance of athlete **B**.

The effects of time can also be present within a single game or set. This is particularly true of performances that run continuously without time outs, such as e-sport sets. In typical e-sport sets, opponents compete without rest until one player resigns. Thus, it is possible to measure shifts in performance within a set itself. For these continuous performance variables, sets can be broken up into segments, and performances in segments can be compared against each other. If particular segments pull for greater performance than others, this indicates a main effect of segment. Alternatively, some players might be more influenced by particular portions of a set than others, resulting in an Athlete × Segment interaction. For the purposes of the current studies, competition effects, Athlete × Set interactions, and Athlete × Segment interactions reflect dynamic influences, with influence of opponent being reflected in competition effects, and the influence of time being reflected in the Athlete × Set and Athlete × Segment interactions.

As outlined above, the goal of the present investigation was to measure the relative magnitude of athlete and dynamic effects on process performance behaviors in competitive environments. Studies 1 and 2 estimated the influences of trait-like differences among performers, competition, and time on professional tennis and e-sport players. To explore whether or not the expertise of the original samples influenced our results, we attempted to replicate the earlier findings with amateur e-sport players with a wide range of skill in Study 3. Because well-practiced behaviors show less random variability (Davids, Glazier, Araújo, & Bartlett, 2003; Müller & Sternad, 2004; Schorer, Baker, Fath, & Jaitner, 2007), we predicted that stable, between-person effects would be more pronounced for experts than for novices. Random variation may cause particular performances to appear to be somewhat better than others, and consequently these random effects would be assigned to dynamic influences, reducing the proportion of variance due to between-person athlete effects.

Study 1

Study 1 examined the influence of trait-like and dynamic variability on athletic performance in a sample of elite tennis players.

Method

Subjects. Subjects were professional tennis players competing at the 2014 Australian Open, a single elimination tournament. Performance measures were collected for all competitors in the men's singles and women's singles divisions of the tournament. Athletes were excluded if (a) they did not play more than one match ($n = 128$) or (b) behavioral data regarding serving speed were missing, which impeded our ability to perform our analyses ($n = 54$). This left us with a total of 74 athletes (50% male; mean age = 26.43; $SD = 3.84$). Participants represented a variety of countries, including France (10.8%), the United States (9.5%), Spain (9.5%), and Germany (6.8%). Performance was measured by IBM, and all data were collected from a publicly accessible database: 2014. ausopen.com.

Measures. Serving speed was chosen as a performance process indicator that was intended to assess an athlete's observation-by-observation performance. Serving speed has high ecological validity as it is a frequently repeated tennis behavior. In addition, a player's serve is solely orchestrated by the server in a way that his aces or volleys are not: These shots rely to some extent on the behavior of the opponent in addition to the behaviors of the athlete herself. Thus, the serve, and more specifically the serving speed, is a behavioral measure least likely to show variation due to opponent. Serving speed was assessed separately for each set within each match. For each athlete, serving speed was the average of all of his or her serves in a set, in kilometers-per-hour. Preliminary analyses were performed for first and second serves separately, yielding nearly identical results. Thus, we report the average of all serves within a set for the sake of concision.

A number of athletes had unequal numbers of sets within matches due to the best-of-three

style of match for women and best-of-five style for men. We could have chosen sets at random within a match when an athlete had played in more than two sets. However, this would have resulted in sets not being fully crossed with athletes, which would have confounded the main effect of set with the Athlete × Set interaction. To maximize our chances of detecting all possible influences on performance, we elected to analyze the first two sets for each match for all subjects.

Statistical analyses. Dynamic variability was calculated using the VARCOMP procedure in SPSS (Version 22.0). Because our opponents were not fully crossed with athletes, we examined the influence of competition effects on process behaviors (e.g., Lakey, Orehek, Hain, & VanVleet, 2010; Lakey & Tanner, 2013). Although fully crossed designs allow for more thorough variance partitioning, few athletic tournaments are structured such that all athletes play each other, and we determined that the high ecological validity of these real-world tournaments compensated for the limitations of the study design. The data were structured as a one-with-many design (Kenny et al., 2006), with Opponents nested within Athletes × Set. Each athlete formed a level of the random Athletes factor; each opponent formed a level of the random Opponents[3] factor; each set formed a level of the random Set factor. Sets represented the replication factor. This design produced five effects: (a) athlete, (b) opponent[4] nested within athlete, (c) set, (d) Athlete × Set, and (e) [Opponent nested within athlete] × Set. Athlete effects reflect stable, trait-like differences in performance. Opponent nested within athlete effects (i.e., competition effects) represent variation in performance across opponents. The Athlete × Set effect represents the interaction of sets with each athlete's performance. For the purposes of this study, opponent nested within athlete, and Athlete × Set, serve as indicators of dynamic variation. The set effect does not represent between-person or within-person influences on performance, and was nonsignificant, and is thus excluded from discussion for brevity. Separate VARCOMPs were performed for males and females to check for gender effects. The results for both groups were identical, and thus we proceeded with a single, mixed sample. This design yields only one observation per cell. Consequently, the opponent nested within Athlete × Set effect, the highest order interaction, served as the error term (Kenny, 1994; Kenny et al., 2006). An effect is significant when its lower bound 95% confidence interval does not include 0. Effects are significantly different from each other when their 95% confidence intervals do not overlap.

Results and Discussion

The goal of Study 1 was to estimate the extent to which professional tennis players' performance varies over time and opponent, reflecting dynamic variability, and the relative magnitude of dynamic and trait-like influences. Variance component estimation (see Table 1) found a significant athlete effect, which explained the majority of the variance in serving speed. In other words, some tennis players tend to always have faster serves than others. In addition, we also detected significant dynamic influences on serving speed. The significant competition effects indicated that the serving speed of tennis players was influenced to some extent by their opponents. The Athlete × Set effect was not significant, indicating that serving speed did not change significantly over the course of sets. The athlete effect was significantly larger than the competition effect ($p < .05$).

The large athlete effects reflected the extent to which some athletes consistently serve at higher speeds than others. Thus, most of the variance in serving speed was due to differences between players, rather than the differences in an athlete's performance from one opponent to the next. For example, Athlete **A** in our sample might consistently serve at 150 KPH, and her serve tends to vary about 5 KPH from one

[3] Within our design, matches are completely confounded within opponent. Although ideally all effects could be measured in a generalizability design, this confounding reflects a real-world reality within sport: One's opponent does not typically change during the course of a single match.

[4] Because opponents are not fully crossed in a one-with-many design, effects due to opponent and effects due to Athlete × Opponent interaction are confounded in a single effect (i.e., competition effect). Different study designs, such as round robin style designs, allow the researcher to distinguish opponent effects from Athlete × Opponent interactions.

Table 1
Variance Components, Confidence Intervals, and Proportion of Variance Explained in Study 1

Serving speed	Variance component	95% confidence interval	Proportion of variance
Between-person			
Athlete	234.63	153.88–315.38	**.86***
Within-person			
Competition	22.23	12.44–32.02	**.08***
Athlete × Set	1.67	−2.09–5.42	**.01**

* $p < .05$.

opponent to the next. Meanwhile, Athlete **B**'s average serve is around 170 KPH, and tends to vary about 10 KPH. Overall, the stable, between-person 20 KPH difference is larger than the 5–10 KPH within-person variation in serving speed that is dynamically elicited by different opponents.

The smaller yet significant competition effects could be conceptualized as strategic variation of serve speed by an athlete based on knowledge of his opponents' individual weaknesses. For one opponent, it might be optimal to always hit faster, whereas for another opponent, slower serves may be an ideal that can be more accurately placed to different spatial locations in the service box (e.g., always to the opponent's backhand). Note that because the main effect of each opponent and the Athlete × Opponent interaction were confounded, we are not able to identify whether particular opponents elicited unique shifts in serving behavior from athletes. Instead, we are able to see that some opponents tended to pull for greater serving speeds than others and that this effect had a meaningful influence on overall serving speeds.

In summary, Study 1 found that variance in serving speed among professional tennis players is predominantly due to trait-like differences in how fast athletes typically serve. A smaller yet significant proportion of variability in serving speed is due to an athlete's opponent—some opponents elicit greater serving speeds than others. The findings of Study 1 are limited because they explore only one process behavior in one sport. Study 2 addresses both of these concerns by examining dynamic variability in the entire spectrum of process behaviors in an entirely different sporting domain.

Study 2

Study 2 attempted to replicate and expand upon the findings of Study 1 by examining the proportion of performance that is explained by dynamic effects in a new domain: electronic sport. Like traditional sport performance, much of the research that has been done surrounding elite video game players compares subjects on traits or characteristics that are stable over time. Recent examples include a comparison of the propensity toward risk-taking of professional Chinese and American e-sport teams (Wang, Xia, & Chen, 2015) and a study associating growth of particular brain regions with career length for professional e-sport players (Hyun et al., 2013). As more resources are invested in e-sport teams and competitions, performance researchers will likely become more interested in understanding factors behind exceptional performance, and developing methods to elicit maximal outcomes. One possible source of performance improvements may come from understanding how dynamic, within-person influences impact performance-process.

With limited literature on dynamic effects in both traditional and electronic sport, we designed Study 2 to compare the statistical properties of performance in tennis with performance in a popular video game. Although Study 1 found significant competition influences, it is possible that those effects are unique to tennis or serving speed, and would not generalize to other performance domains. Some readers may be skeptical about comparing domains as disparate as tennis and electronic sport. However, finding similarities in how performance behaviors operate in two very different domains would offer interesting insights about perfor-

mance in general that may not be as apparent if tennis were compared with a similar sport. Thus, although the status of electronic sport in comparison with traditional sport is a source of ongoing controversy (Jonasson & Thiborg, 2010; Witkowski, 2012), we believe that comparing the statistical properties of performance between tennis and e-sport professionals will provide interesting insights for both domains.

Method

Materials. Study 2 examined performance consistency in world-class players of the video game StarCraft 2 (Blizzard Entertainment, 2013). StarCraft 2 is a real-time strategy game in which players collect resources, which allow them to build a base and manufacture military units, which are then sent to fight with the opponent's units. The game comes to an end when either (a) a player's entire army and base are destroyed or (b) a player resigns. Typically, players resign when it is clear that they cannot recover from an opponent's attack.

Participants. Our sample included elite StarCraft 2 video game players who participated in the second season of the 2014 World Championship Series ($n = 32$). Players competed in best-of-three-set style matches. The mean age of this group was 21.35 ($SD = 2.08$) years. The sample was 100% Korean. Data were collected from official replays of tournament matches, which were made publically available by the hosting organization and can be found at wcs.battle.net.

Measures. Our process performance variable of interest was actions per minute (APM), which is the total number of mouse and keyboard inputs a player makes throughout the match divided by the total match length (in minutes). APM is a unique behavioral measurement in that it captures the entire range of possible behaviors within this e-sport. Thus, Study 2 differs from Study 1 in that Study 2 examines variability in the frequency of all behaviors that encompass the process of playing StarCraft 2, rather than a subset of behaviors. We are more likely to see dynamic variance by chance in a single process performance indicator, but perhaps less likely to detect significant dynamic effects when looking at all possible behaviors combined. Thus, this study represents another strong test of the importance of dynamic variability in performance behaviors.

APM is useful because it encapsulates all possible performance behaviors, yet it is limited because it also includes unnecessary repetitions in keystrokes or mouse clicks as well as mistakes. Although it may be possible to conduct an evaluative screening on APM to count or exclude poor inputs, we decided against this. Although some players may inflate their APM, it would be a natural variation in the performance of players, and thus is useful in a study exploring how one might measure performance shifts across opponents and over time.

Another difference between the performance variables is that APM is a continuous-time measurement, whereas serving speed is represented by a discrete-time measurement. That is, APM is measured over the course of minutes, whereas serving speed consists of the separate events "first serve," "second serve," and so on. Because APM can meaningfully shift from moment to moment, we segmented each match into 10 portions of equal length to measure changes in APM over the course of each match; each portion represented 10% of the total time in each match. We created aggregations of these segments to reduce the complexity of the design and to reduce random microfluctuations. Because we had no a priori hypotheses regarding appropriate aggregation methods, we created 100 random aggregation patterns. Each pattern combined the 10 segments into one of two aggregates, with no segment appearing in both aggregates. As a result, we estimated change in APM over the course of a match 100 times for each individual in our sample. Although matches were in a best-of-three format, we used the first two sets of each match to be consistent with Study 1.

Statistical analyses. As in Study 1, we used the VARCOMP procedure in SPSS (Version 22.0). However, because of the differences between serving speed and APM as performance variables, the study design was slightly different. The data were structured as a one-with-many design (Kenny et al., 2006), with [Opponents nested within Athletes] × Set × Segment. Each athlete formed a level of the random Athletes factor; each opponent formed a level of the random Opponents[1] factor; each set formed a level of the random Set factor; and each segment formed a level of the random

Segment factor. The random aggregates of time segments served as the replication factor. This design produced seven effects: (a) athlete, (b) opponents[2] nested within athletes, (c) set, (d) segment, (e) Athlete × Set, (f) Athlete × Segment, and (g) [Opponents nested within athlete] × Set × Segment. As before, athlete effects reflected stable, trait-like differences in performance. Opponent nested within athlete effects (i.e., competition effects) represent variation in performance as athletes move between opponents. The Athlete × Set effects are the interaction between particular players and particular sets. Finally, the Athlete × Segment effect represents the interaction of the time course of matches with each athlete's performance. The Set and Segment effects do not reflect between- or within-person influences on performance and were nonsignificant, and are thus excluded from discussion for the sake of brevity. For the purposes of this study, competition effects, Athlete × Segment, and Athlete × Set operate as indicators of dynamic variation. This design yields only one observation per cell, and thus the highest order interaction was the error term (Kenny, 1994; Kenny et al., 2006). Because we had 100 estimations of each effect, we used those estimates to construct 95% confidence intervals around the median variance component estimate using the percentile method. An effect is significant when its lower bound 95% confidence interval does not include 0. Effects are significantly different when their 95% confidence intervals do not overlap.

Results and Discussion

In Study 2, we examined the extent to which the performance of professional e-sport players was dynamically influenced. Replicating Study 1, we detected both stable athlete effects and dynamic influences on performance (Table 2). The largest influence on APM was the trait-like athlete effect, meaning that, on average, some players tended to produce more keyboard and mouse inputs over the course of a game than others. There were also two sources of dynamic influences: competition and athlete x set effects. Put another way, the APM of professional e-sport players was influenced in part by the competitor, and also by the set within a match. For example, the first set may pull for unusually strong APM in some players, but not others. The athlete effect explained the majority of the variance in APM, and was significantly larger than competition effects and Athlete × Set effects ($p < .05$). The Athlete × Set interaction was significantly larger than the competition effect ($p < .05$).

The results of Study 2 represent a partial replication of Study 1. Trait-like differences accounted for the vast majority of the variance in both tennis serving speed and electronic sport actions per minute. In addition, both studies found small but significant dynamic effects on process performance variables. Nevertheless, the sources of these effects differed. In Study 1, all of the dynamic variation was due to competition effects. For both tennis and StarCraft 2 players, performance was influenced by their

Table 2
Median Estimates of Variance Components, Confidence Intervals, and Proportion of Variance Explained in Study 2

Actions per Minute	Variance component (median)	95% confidence interval	Proportion of variance
Between-person			
Athlete	4409.33	4218.24–4434.86	**.77***
Within-person			
Competition	396.58	323.35–428.44	**.06***
Athlete × Set	544.02	470.78–575.87	**.09***
Athlete × Segment	33.43	.00–502.42	**.01**

Note. Negative variance component estimates are constrained to zero by SPSS at the end of the VARCOMP operation. Because we constructed 95% confidence intervals using these estimates, the lower bound will always be constrained to zero.
* $p < .05$.

opponent, such that some opponents elicited faster serves and APM than others. However e-sport players, but not tennis players, were also influenced in such a way that particular sets pulled for stronger performance in particular players. There was no significant Athlete × Set effect in our tennis sample.

Competition effects for e-sport players reflect the extent to which some opponents pull for more APM than others. This effect may reflect a deliberate choice by players to enact particular strategies based upon knowledge of their opponents. For example, in trying to exploit his opponent's perceived weaknesses, player **A** may deploy more aggressive strategies against opponent **B**, while using more conservative strategies against opponent **C**. If more aggressive strategies require frequent, precisely controlled attacks, they may require consistently higher APM to execute than more conservative strategies.

E-Sport performance was also influenced by an interaction between the players and particular sets, meaning that the first set may always elicit more APM in some players, but not others. It is possible that this Athlete × Set interaction is a statistical representation of varying strategy from set to set. For instance, in a typical match Player **A** may characteristically utilize a rapid attack strategy requiring high APM for a short amount of time in the first set, while using a slower strategy requiring a more relaxed APM over a longer period in the second set, while Player **B** might engage in a high APM strategy in second sets, but not first. This strategy variation by each athlete represents an Athlete × Set interaction.

Study 2 replicated Study 1's findings that elite competitive performance is primarily a function of trait-like differences in the speed of the performers. However, in both samples, performance was also dynamically influenced. Despite these compelling findings, Studies 1 and 2 featured professionals, representing only the top of the range of ability in their respective domains. Although we found common effects between both samples, it is unknown whether large trait-like effects and smaller yet significant dynamic influences are features of elite performance or of performance in general. Thus, in Study 3, we analyzed the performance of amateur e-sport players in an attempt to detect dynamic influences.

Study 3

In the third study, we expanded upon Study 2 by attempting to measure dynamic variability in the performance of amateur StarCraft 2 players across a large spectrum of skill. Performance process behaviors have been shown to feature less random variation with high expertise (Davids et al., 2003; Müller & Sternad, 2004; Schorer et al., 2007). Consequently, we predicted that the more experienced players would show stronger athlete effects than the novices. Finding differences in the stable and dynamic effects of novices and experts in Study 3 would suggest that our earlier results reflected elite skill. On the other hand, if the results of Study 3 converged with those of Studies 1 and 2, we would have evidence that the larger athlete effects and significant but smaller competition effects are a part of performance in general. As we were particularly interested in how expertise impacts the relative magnitudes of athlete and competition effects, we compared results across skill levels.

This study has implications for research on the effects of video game playing on cognitive processes, which has been criticized for violating the rules of experimental design by targeting experienced video game players (Boot, Blakely, & Simons, 2011) and relying on self-reports of expertise rather than objective metrics (Latham, Patston, & Tippett, 2013). Comparing the findings of Study 2's professional sample with Study 3's amateur sample may shed light on how to define video game experience more clearly.

Method

Materials. Study 3 examined performance in amateur players of StarCraft 2, the e-sport described in Study 2.

Participants. Our sample included 289 amateur StarCraft 2 players. StarCraft 2 features an online multiplayer matching system that matches players on the basis of their performance history. Players are divided into seven leagues on the basis of their skill relative to other players. For the current study, between 34 and 51 players from each league were sampled.

Match data were gathered from a publically accessible StarCraft 2 replay website where players post their match replays and can com-

pare with other players: ggtracker.net. First, 100 replays from each league were chosen at random from the database. Matches that were shorter than 5 minutes were excluded. If at least 30 players appeared in 2 of the matches chosen at random, then the drawing was complete. If fewer than 30 players appeared in 2 matches, then another 50 matches were chosen at random, with care taken not to redraw the same matches. This process was repeated to select matches from each league. Because players are only identified by their in-game handle, demographic information for the selected players is unknown. Due to limitations of the database, we were only able to get one match per athlete–opponent pair.

Measures. Our process performance variable, actions per minute, was identical to that used in Study 2. We used the same segment aggregation process as well.

Statistical analyses. The design of Study 3 differed slightly from that of Study 2 because of differences in the data available. Because each player had only one match with each opponent, we are unable to detect set or Athlete × Set effects. Thus, the design has five effects: (a) athlete, (b) opponent nested within athlete, (c) segment, (d) Segment × Athlete, and (e) [Opponent nested within athlete] × Segment. We ran the VARCOMP procedure (SPSS 22.0) on each league's sample separately. As before, we omit discussion of the segment effect because it is not significant and is not the focus of this article. As in Study 2, we had 100 estimates of each effect because of the segment aggregation procedure, and these 100 estimates were used to construct 95% confidence intervals. An effect is significant if its 95% confidence interval does not include 0. Effects are significantly different from each other if their 95% confidence intervals do not overlap.

In addition to estimating effects for each sample, we were also interested in potential differences in the proportions of variance attributable to effects between samples. Consequently, we constructed 95% confidence intervals around the median proportion of variance estimate using the same method that we used for the variance component estimations. Groups differ in the proportion of variance attributable to particular effects if the 95% confidence intervals of their proportions do not overlap.

Results and Discussion

In Studies 1 and 2 we detected large and stable athlete effects on performance, and smaller, but significant, dynamic influences—not knowing if these effects were a property of performance in general, or an attribute of expert performance specifically. The goal of Study 3 was to determine if these patterns of influences on performance would be apparent across a range of skill levels, and they were. Across the entire range of amateur skill levels, there were both large athlete effect and smaller, but significant, dynamic effects, consistent with the first two studies (see Table 3). Within the dynamic influences, as in Study 2, a significant portion of performance was attributable to competition effects. Thus, regardless of skill level, some opponents elicited more APM than others. Replicating Studies 1 and 2, the athlete effect was significantly larger than the competition effect ($p < .05$). As in Study 2, there were no significant Athlete × Segment interactions.

In addition to identifying significant influences on performance, we also looked within proportions of athlete and competition effect estimates to see if there were differences between leagues. Interestingly, there were no differences between leagues in either effect, even between the highest and lowest skill levels. On the other hand, examination of the variance totals demonstrated that there were differences in the players assigned to each league. On average, there tended to be much more variety in the performances of players in the platinum league compared with that of the bronze league, for example. Yet although the players in each league were different, and their performances were different, the magnitude of athlete and competition effects was consistent across all samples. This finding, in conjunction with the similar findings of Studies 1 and 2, provided evidence that dynamic effects are a component of performance in general, rather than an aspect of elite performance.

The similarity of findings in Studies 2 and 3 suggested that, although much smaller than athlete effects, competition effects may be influential across all levels of expertise within e-sport performance. We hypothesized above that competition influences may in part reflect choices in the strategies deployed by players. Nevertheless, although it is very likely that experienced

Table 3
Median Estimates of Variance Components, Confidence Intervals, and Proportion of Variance Explained in Study 3

Actions per minute	Variance component (median)	95% confidence interval for variance components	Proportion of variance (median)	95% confidence interval for proportion of variance
Between-person				
Athlete effects				
Bronze (novices)	1082.72	985.51–1102.30	**.74***	.57–.77
Silver	1748.90	1694.99–1783.09	**.66***	.51–.71
Gold	1948.97	1753.85–2018.70	**.70***	.52–.75
Platinum	3106.08	2936.65–3153.57	**.74***	.64–.77
Diamond	3179.98	2942.05–3263.68	**.78***	.66–.82
Masters	2907.63	2602.91–3002.88	**.76***	.62–.80
Grand Masters (experts)	2528.53	2199.27–2586.96	**.79***	.61–.83
Within-person				
Competition effects				
Bronze (novices)	215.25	152.79–246.73	**.15***	.09–.17
Silver	405.65	304.59–507.81	**.15***	.10–.19
Gold	394.66	310.93–445.62	**.14***	.09–.16
Platinum	616.59	477.75–720.85	**.15***	.10–.17
Diamond	357.34	224.47–454.24	**.09***	.05–.11
Masters	446.28	296.49–512.55	**.12***	.07–.14
Grand Masters (experts)	270.12	143.52–331.75	**.08***	.04–.10
Athlete × Segment effects				
Bronze (novices)	39.17	.00–263.64	**.03**	.00–.15
Silver	63.38	.00–232.12	**.02**	.00–.08
Gold	139.46	.00–570.93	**.05**	.00–.17
Platinum	94.98	.00–476.36	**.02**	.00–.11
Diamond	167.34	.00–748.12	**.04**	.00–.16
Masters	190.50	.00–803.93	**.05**	.00–.19
Grand Masters (experts)	116.85	.00–841.20	**.04**	.00–.23
Total variance[1]				
Bronze (novices)	1459.62	1426.17–1746.83		
Silver	2664.21	2529.93–3379.28		
Gold	2806.30	2690.62–3471.33		
Platinum	4218.61	4107.89–4739.07		
Diamond	4094.45	3966.34–4563.72		
Masters	3852.10	3727.23–4268.15		
Grand Masters (experts)	3198.79	3116.68–3632.50		

Note. Negative variance component estimates are constrained to zero by SPSS at the end of the VARCOMP operation. Because we constructed 95% confidence intervals using these estimates, the lower bound will always be constrained to zero.
[1] Total variance includes the set effect and error (not shown).
* $p < .05$.

e-sport players deploy varied strategies from match to match, it seems less likely that novices do the same. It is possible that the source of dynamic effects shifts over time from inconsistency due to inexperience (i.e., learning curve) to conscious modification of APM as a player gains experience. Unfortunately, because our data were cross-sectional, we were unable to address this hypothesis. Additionally, having multiple observations with each opponent would have allowed us to distinguish APM due to occasion from APM due to opponent. APM influences due to occasion are likely to have more impact at lower levels of skill, when players are still mastering keyboard commands. Thus, this confounded influence may have had an impact on our estimates of competition effects. However, because the estimates of competition effects did not differ between leagues, this seems unlikely.

Our findings diverged from previous findings suggesting that random variability is less pro-

nounced in more experienced performers (Davids et al., 2003; Müller & Sternad, 2004; Schorer et al., 2007), in that our novices showed the same structure of stable and dynamic influences as our experts. The difference may derive from differences in study focus, that is, frequency of performance behaviors as opposed to motor execution of performance behaviors. For example, Schorer et al. (2007) examined variability in arm movement patterns when participants of various expertise levels made a series of handball throws. It is possible that athlete and competition effects behave differently depending on the performance variable of interest.

The results of Study 3 complement ongoing research with video game players to understand cognitive processes such as attention and visual processing. Often, this research relies on comparing experienced players with novices (e.g., Glass, Maddox, & Love, 2013) or video game players with nonplayers (e.g., Irons, Remington, & McLean, 2011). This literature has become controversial, however, because of lack of agreement on what constitutes expertise in research on video game players (Latham, Patston, & Tippett, 2013). For example, Basak, Boot, Voss, and Kramer (2008) trained older adults on a video game for 23.5 hours before comparing a host of cognitive processes to those of controls, whereas Glass and colleagues (2013) compared players given 40 hours of training with nonplayers. Similarly, there are concerns that the results of research on experienced video gamers may have been impacted by demand characteristics, particularly if participants knew why they were recruited for the studies. Given that expert performers are ideal for understanding links between video game playing and cognitive skill Towne, Ericsson, and Sumner (2014), it is vital that researchers have empirically supported methods of distinguishing experts from nonexperts. The present finding that the performance behaviors of experienced and novice players have very similar magnitudes of athlete and competition effects highlights the difficulty of defining what expertise with a video game is. Looking simply at variation in performance behaviors will likely be inadequate.

General Discussion

For the last several decades, the sport psychology literature has explored the extent to which trait-like differences in characteristics such as affect and self-esteem predict differences in performance outcomes. More recently, however, we see investigations of how dynamic variation in psychological processes such as anxiety and affect can predict performance outcomes. Although there have been attempts to link variation in intrapersonal states with performance outcomes, it would be important to attempt to identify the extent to which performance process behaviors themselves vary across time and opponents. In particular, it is critical to understand how performance-process behaviors vary within individuals and the relative magnitude of this dynamic variation. The current studies offer preliminary evidence of significant variation in performance process behaviors across opponents and over time. These results were consistent across two very different sporting domains, suggesting generalizability.

Across three studies, trait-like athlete effects were the predominant influence on performance. Replicating this finding in two distinct domains, as well as across levels of expertise, suggested that these stable effects may be an important feature of performance in general, beyond tennis and e-sport. It is possible that a large portion of trait-like influences stems from physical performance in general. The repetitive movements and planned behaviors involved in performance lend themselves to consistency. Furthermore, future research should explore factors that enhance or inhibit the mostly consistent nature of performance and whether performing close to an athlete's overall average is beneficial to performance outcome. Put another way, is being more consistent, and varying less, a valuable skill in sport performance? Findings of these studies may have implications for training programs. Athletes may benefit from learning to consciously alter their consistency.

Although the majority of the variance in performance for tennis and e-sport was attributable to stable differences between performers, we reliably detected a significant influence of opponent, whereby some opponents pulled for faster serves and APM than others. These competition effects were statistically distinguishable from trait-like differences, which are stable over opponent and time. It is possible that the significant competition influences on process-related behavior represent conscious, strategic manipulation. It is not difficult to imagine a tennis

player purposefully varying her serving speed to target a perceived weakness in her opponent, or a StarCraft 2 player utilizing strategies with varying APM against different opponents. Unfortunately, because the Athlete × Opponent interaction was confounded with the opponent effect into competition effects, we were unable to determine whether, for example, some opponents pull for more APM in performance across all players, or whether shifts in performance are due to idiosyncratic relationships between particular athletes and particular opponents.

For professional e-sport players, but not professional tennis players, our results showed a significant Athlete × Set interaction, meaning that particular sets pulled for different levels of APM for particular athletes. In contrast, both samples had significant competition influences. It is possible that the differences in dynamic variance components between tennis and e-sport professionals may be due to differences in tennis and StarCraft 2 performance variables. In tennis, the serve is one of a constellation of behaviors that make up a match. In StarCraft 2 and e-sport in general, keyboard and mouse actions represent all of the possible process-related behaviors. We may have been able to detect an Athlete × Set interaction if we were able to examine all possible behaviors within tennis, or alternatively, these effects may disappear if we were to examine only a particular input or subset of inputs by e-sport players. In addition, another possible reason for the difference is that APM in StarCraft 2 is measured over time, whereas serving speed represents discrete events. We encourage future researchers to continue to develop performance metrics, particularly for e-sport.

Given the relative magnitude of the variance explained by athlete and competition effects, we can conceptualize performance, at least for tennis and e-sport players, to be determined primarily by stable differences in ability between performers, but also by the small but significant influence of the competitor. Furthermore, because there were similar magnitudes of effects at all levels of experience as examined in Study 3, it is possible that this structure of influences generalizes to performance in general.

To date, a handful of studies have investigated dynamic effects in sport. The current investigation contributes to this literature by underscoring the importance of considering dynamic effects in performance itself, in addition to dynamic effects on psychological processes. For example, Gaudreau, Nicholls, and Levy (2010) reported that dynamic shifts in golfers' coping strategies predict performance outcome. Similarly, Doron and Gaudreau (2014) linked prior performance outcomes to later perceived control and affect. Even so, these studies focus on variability in psychological processes rather than performance itself. The present study documented dynamic effects in performance process in two different domains, tennis and e-sport, and across a range of skill levels, from novice to professional, in one domain. Future investigations should utilize dynamic effects in both psychological variables and performance itself in order to understand the role that within-person variation can have on performance outcomes. For example, a study of tennis players could investigate whether dynamic shifts in affect and anxiety could be linked to dynamic shifts in serving speed and measure the impact of both dynamic variation of psychological processes and performance on the outcome of matches.

The results of the current study suggested that competitive performance-process in e-sport is subject to significant dynamic variation. Given earlier findings, it is important to consider a potential effect of solo gameplay. In a study on the impact of social interaction on performance, barely acquainted dyad members were asked to play a team-based video game together, and rate the affect and feelings of supportedness elicited by their partners (Woods, Lakey, & Sain, 2015; Study 3). Performance in the video game was mostly attributable to stable differences in skill among participants, but another large portion of the variance was attributable to interactions between dyad members. When a dyad member elicited unusually favorable affect and high feelings of supportedness, that dyad member also elicited unusually strong performance in the participant. In the cooperative video game, dynamic influences accounted for 35% of the variance in performance, whereas in our samples, dynamic influences never accounted for more than 15%. Although these findings may simply result from the use of different video games and different performance metrics, it is important to consider that cooperative performance could elicit more dynamic variability than the solo performances included in the cur-

rent study. Future research should investigate the extent to which the magnitude of dynamic influences is affected by solo, dyad, and team performances, such as doubles tennis.

Furthermore, since dynamic variation effects have been reported outside of sport performance, contrasting findings on dynamic variation on performance across different tasks may yield implications for future investigations. Gross and colleagues (2015) demonstrated that student performance on quizzes could be forecasted in part by idiosyncratic preferences for particular professors. When a professor elicited unusually high evaluations from a student, that student performed unusually well on that professor's quiz, beyond his or her generally tendency to perform well on all quizzes, and beyond the professor's tendency to elicit higher scores by all students. Research into dynamic variability in ordinary social interaction has demonstrated that most of the variance in perceived support, affect, and negative affect is attributable to the interaction partner, whereas positive affect is approximately equally socially influenced and trait-like (Lakey & Tanner, 2013). At the dynamic level, all of these constructs are highly correlated, meaning that interlocutors who elicit favorable affect also elicit stronger feelings of being supported. When dynamic variance was controlled, correlations between trait-level tendencies to view others as supportive and to experience favorable affect were either nonsignificant or inconsistent across studies. Understanding differences and similarities between ordinary social interaction and purposeful competition may shed light into how purposeful performance works, and how training might be enhanced.

Significant dynamic influences across competitive domains and skill levels raise implications for future investigations of training programs. Because across all studies, some opponents elicited stronger performances than others, athletes may benefit from being assigned training partners who elicit varying levels of change in a player's typical performance, for example, one who elicits much higher than average serving speeds. Additionally, because some opponents do pull for greater performances than others, it seems that athletes would benefit from variety in practice partners more generally, in order to learn to mitigate undue negative influences.

There are several limitations to the current investigation. First, our research design did not allow for opponents to be fully crossed with athletes, and thus the main effect of opponent was confounded with the athlete opponent interaction. Future investigations could utilize designs like a round robin that allow for separating these two effects. Second, because tennis and e-sport professionals engage in quite different process-related behaviors, we had to roughly equate serving speed in tennis with APM in e-sport as process behaviors, noting that whereas serving speed is only one of many tennis behaviors, APM represents the entire spectrum of e-sport behaviors. Future research into e-sport performance should attempt to create subsets of input behaviors that may more closely be equated with occasional behaviors like tennis serves. Alternatively, researchers might develop a performance metric that integrates the many aspects of tennis play, rather than a single metric such as serves. A third limitation is that, because Study 3 relied on only one observation per opponent, we were not able to replicate the Athlete $\times$ Set effect found in Study 2. Nevertheless, even with these differences, we replicated findings showing both strong athlete effects and significant competition effects in tennis professionals, e-sport professionals, and e-sport amateurs. Finally, our research was limited in that we did not link dynamic effects on performance process to performance outcome, which will be an important next step if such effects do affect outcome.

Sport psychology research has been dominated by examinations of how trait-like differences among athletes can explain differences in performance outcomes. Yet, a growing body of research has begun to investigate how changes within athletes' psychological processes can affect athletic performance outcomes. What has not been explored is the extent to which performance-process behaviors in sport also change over opponents and time. In three studies, we reported preliminary evidence of important variability in the performance of elite professional athletes as well as amateur e-sport players. Study 1 found large, stable athlete effects and significant, dynamic variation in serving speed by elite tennis players such that some opponents elicited faster serves than others. Study 2 reported similarly large athlete effects and significant, dynamic effects in the fre-

quency of keyboard and mouse inputs by professional e-sport players, with dynamic variability once again reflecting changes in opponent. Study 3 replicated earlier findings with professional performers in a sample of amateur e-sport players over a range of skill levels. Future research may benefit from integrating measurement of dynamic variation in process-related behaviors in the quest to develop more effective interventions to optimize performance outcomes across a range of behaviors.

References

Aguilar, R., Jiménez, M., & Alvero-Cruz, J. R. (2013). Testosterone, cortisol and anxiety in elite field hockey players. *Physiology & Behavior, 119,* 38–42. http://dx.doi.org/10.1016/j.physbeh.2013.05.043

Anshel, M. H., & Wells, B. (2000). Sources of acute stress and coping styles in competitive sport. *Anxiety, Stress, and Coping, 13,* 1–26. http://dx.doi.org/10.1080/10615800008248331

Basak, C., Boot, W. R., Voss, M. W., & Kramer, A. F. (2008). Can training in a real-time strategy video game attenuate cognitive decline in older adults? *Psychology and Aging, 23,* 765–777. http://dx.doi.org/10.1037/a0013494

Beedie, C. J., Terry, P. C., & Lane, A. M. (2000). The profile of mood states and athletic performance: Two meta-analyses. *Journal of Applied Sport Psychology, 12,* 49–68. http://dx.doi.org/10.1080/10413200008404213

Blizzard Entertainment. (2013). StarCraft 2: Heart of the swarm [Computer software on DVD-ROM]. Irvine, CA: Blizzard Entertainment.

Boot, W. R., Blakely, D. P., & Simons, D. J. (2011). Do action video games improve perception and cognition? *Frontiers in Psychology, 2,* 226. http://dx.doi.org/10.3389/fpsyg.2011.00226

Coussens, A. H., Rees, T., & Freeman, P. (2015). Applying generalizability theory to examine the antecedents of perceived coach support. *Journal of Sport & Exercise Psychology, 37,* 51–62. http://dx.doi.org/10.1123/jsep.2014-0087XXX

Davids, K., Glazier, P., Araújo, D., & Bartlett, R. (2003). Movement systems as dynamical systems: The functional role of variability and its implications for sports medicine. *Sports Medicine, 33,* 245–260. http://dx.doi.org/10.2165/00007256-200333040-00001

Doron, J., & Gaudreau, P. (2014). A point-by-point analysis of performance in a fencing match: Psychological processes associated with winning and losing streaks. *Journal of Sport & Exercise Psychology, 36,* 3–13. http://dx.doi.org/10.1123/jsep.2013-0043

Filaire, E., Alix, D., Ferrand, C., & Verger, M. (2009). Psychophysiological stress in tennis players during the first single match of a tournament. *Psychoneuroendocrinology, 34,* 150–157. http://dx.doi.org/10.1016/j.psyneuen.2008.08.022

Gaudreau, P., Nicholls, A., & Levy, A. R. (2010). The ups and downs of coping and sport achievement: An episodic process analysis of within-person associations. *Journal of Sport & Exercise Psychology, 32,* 298–311.

Glass, B. D., Maddox, W. T., & Love, B. C. (2013). Real-time strategy game training: Emergence of a cognitive flexibility trait. *PLoS ONE, 8*(8), e70350. http://dx.doi.org/10.1371/journal.pone.0070350

Gross, J., Lakey, B., Lucas, J. L., LaCross, R., Plotkowski, A. R., & Winegard, B. (2015). Forecasting the student–professor matches that result in unusually effective teaching. *British Journal of Educational Psychology, 85,* 19–32. http://dx.doi.org/10.1111/bjep.12049

Hagtvet, K. A., & Hanin, Y. L. (2007). Consistency of performance-related emotions in elite athletes: Generalizability theory applied to the IZOF model. *Psychology of Sport and Exercise, 8,* 47–72. http://dx.doi.org/10.1016/j.psychsport.2005.12.002

Hanin, Y. L. (1997). Emotions and athletic performance: Individual zones of optimal functioning model. *European Yearbook of Sport Psychology, 1,* 29–72.

Hyun, G. J., Shin, Y. W., Kim, B. N., Cheong, J. H., Jin, S. N., & Han, D. H. (2013). Increased cortical thickness in professional on-line gamers. *Psychiatry Investigation, 10,* 388–392. http://dx.doi.org/10.4306/pi.2013.10.4.388

Irons, J. L., Remington, R. W., & McLean, J. P. (2011). Not so fast: Rethinking the effects of action video games on attentional capacity. *Australian Journal of Psychology, 63,* 224–231. http://dx.doi.org/10.1111/j.1742-9536.2011.00001.x

Jokela, M., & Hanin, Y. L. (1999). Does the individual zones of optimal functioning model discriminate between successful and less successful athletes? A meta-analysis. *Journal of Sports Sciences, 17,* 873–887. http://dx.doi.org/10.1080/026404199365434

Jonasson, K., & Thiborg, J. (2010). Electronic sport and its impact on future sport. *Sport in Society: Culture, Commerce, Media. Politics, 13,* 287–299. http://dx.doi.org/10.1080/17430430903522996

Kenny, D. A. (1994). *Interpersonal perception: A social relations analysis*. New York, NY: Guilford Press.

Kenny, D. A., Kashy, D. A., & Cook, W. L. (2006). *Dyadic data analysis*. New York, NY: Guilford Press.

Lakey, B., Orehek, E., Hain, K. L., & Van Vleet, M. (2010). Enacted support's links to negative affect and perceived support are more consistent with

theory when social influences are isolated from trait influences. *Personality and Social Psychology Bulletin, 36,* 132–142. http://dx.doi.org/10.1177/0146167209349375

Lakey, B., & Tanner, S. (2013). Social influences in negative thinking and affect. *Cognitive Therapy and Research, 37,* 160–172. http://dx.doi.org/10.1007/s10608-012-9444-9

Latham, A. J., Patston, L. L., & Tippett, L. J. (2013). Just how expert are "expert" video-game players? Assessing the experience and expertise of video-game players across "action" video-game genres. *Frontiers in Psychology, 4,* 941. http://dx.doi.org/10.3389/fpsyg.2013.00941

Martens, R., Burton, D., Vealey, R. S., Bump, L. A., & Smith, D. E. (1990). Development and validation of the Competitive State Anxiety Inventory-2. In R. Martens, R. S. Vealey, & D. Burton (Eds.), *Competitive anxiety in sport* (pp. 117–190). Champaign, IL: Human Kinetics.

Müller, H., & Sternad, D. (2004). Decomposition of variability in the execution of goal-oriented tasks: Three components of skill improvement. *Journal of Experimental Psychology: Human Perception and Performance, 30,* 212–233. http://dx.doi.org/10.1037/0096-1523.30.1.212

Rees, T., Freeman, P., Bell, S., & Bunney, R. (2012). Three generalizability studies of the components of perceived coach support. *Journal of Sport & Exercise Psychology, 34,* 238–251.

Schorer, J., Baker, J., Fath, F., & Jaitner, T. (2007). Identification of interindividual and intraindividual movement patterns in handball players of varying expertise levels. *Journal of Motor Behavior, 39,* 409–421. http://dx.doi.org/10.3200/JMBR.39.5.409-422

Shavelson, R. J., & Webb, N. M. (1991). *Generalizability theory: A primer*. Newbury Park, CA: Sage.

Towne, T. J., Ericsson, K. A., & 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

Wang, H., Xia, B., & Chen, Z. (2015). Cultural difference on team performance between Chinese and Americans in multiplayer online battle arena games. In P. L. P. Rau (Ed.), *Cross-cultural design applications in mobile interaction, education, health, transport and cultural heritage* (pp. 374–383). New York, NY: Springer International Publishing. http://dx.doi.org/10.1007/978-3-319-20934-0_35

Witkowski, E. (2012). On the digital playing field: How we "do sport" with networked computer games. *Games and Culture, 7,* 349–374. http://dx.doi.org/10.1177/1555412012454222

Woods, W. C., Lakey, B., & Sain, T. (2015). The role of ordinary conversation and shared activity in the main effect between perceived support and affect. *European Journal of Social Psychology*. Advance online publication. http://dx.doi.org/10.1002/ejsp.2149

Received December 7, 2015
Revision received April 16, 2016
Accepted May 4, 2016 ■