Article

Shared Zones of Optimal Functioning (SZOF): A Framework to Capture Peak Performance, Momentum, Psycho-Bio-Social Synchrony and Leader-Follower Dynamics in Teams

Filho, Edson

Shared Zones of Optimal Functioning (SZOF): A Framework to Capture Peak Performance, Momentum, Psycho-Bio-Social Synchrony and Leader-Follower Dynamics in Teams

Edson Filho

School of Psychology, University of Central Lancashire

***Corresponding Author:**

Edson Filho, PhD.

Lecturer in Sport and Exercise Psychology

School of Psychology

University of Central Lancashire

Darwin Building 114

Preston PR1 2HE

United Kingdom

Tel: +44 (0) 1772893436

Email: efilho@uclan.ac.uk

Abstract

By bridging the literature on Shared Mental Models and the Individual Zones of Optimal Functioning (IZOF), I advance a new framework called the Shared Zones of Optimal Functioning (SZOF). The SZOF is a probabilistic methodology designed to (a) capture optimal and sub-optimal performance experiences in teams, (b) track team momentum through the analysis of within-team performance fluctuations, and (c) estimate within-team psycho-bio-social synchrony and leader-follower dynamics (i.e., leader-follower dichotomy; shared-leadership). To test the SZOF framework, three dyadic juggling teams were asked to juggle for 60 trials, while having their performance, arousal, pleasantness and attentional levels recorded. Ordinal logistic regression, frequency counts, and cross-correlation analyses revealed that each team showed idiosyncratic affective and attentional levels linked to optimal performance, team momentum patterns, and leader-follower dynamics. The implications of these findings for the development of high-performing teams and specific avenues of future research are discussed throughout.

Keywords: Shared Zones of Optimal Functioning; Individual Zones of Optimal Functioning; Shared Mental Models; Group Dynamics; Leadership.

Shared Zones of Optimal Functioning (SZOF): A Framework to Capture Peak Performance, Momentum, Psycho-Bio-Social Synchrony and Leader-Follower Dynamics in Teams

The cross-fertilization of different theories, methodologies, and disciplines allows for the birth of novel ideas and domains of knowledge (Popper, 2005). Bearing this in mind, I have juxtaposed the literature of two well-developed fields in Sport, Exercise and Performance Psychology, namely Shared Mental Models (SMM) and the Individual Zones of Optimal Functioning (IZOF), to propose a new applied framework called the Shared Zones of Optimal Functioning (SZOF). Teamwork is essential to performance in sports and beyond, and the SZOF framework detailed herein offers a theoretical and applied platform to capture optimal and sub-optimal performance experiences, and estimate within-team performance fluctuations, psycho-bio-social synchrony levels, and leader-follower dynamics in teams.

Shared Mental Models

SMM consist of different types of knowledge (know-what; know-why; know-where; know-when; know-how) held in common by a team (Filho, 2019), which in turn have been defined as a collection of individuals united by shared goals (Hackman & Wageman, 2005). SMM vary in quality and quantity and reflect psycho-bio-social states and patterns in teams (see *reflective indicators* in Hoyle, 2011). To perform optimally, teams must share high-quality knowledge which enables performance, as opposed to low-quality knowledge which hinders performance (Lim & Klein, 2006). Furthermore, SMM are a cross-level property insofar that teammates also share knowledge about the individuals in the team, the team as a whole, and the broader performance context (Filho, 2019). In other words, individuals are nested within teams, which in turn are bounded to a specific performance context (e.g., military, sports).

Previous research on SMM is extensive and has been reviewed in detail elsewhere (for reviews see Filho & Tenenbaum, 2012; Mohammed, Ferzandi, & Hamilton, 2010). Particularly relevant to the SZOF, SMM have been found to predict team performance and be reflected through the synchronization of psycho-bio-social states and patterns (Filho et al., 2016; Filho, Pierini, Robazza, Tenenbaum, & Bertollo, 2017). SMM facilitates performance because teammates are able to “think as a team” to reach the right decisions (know-what) for the right reasons (know-why) in order to do the right thing (know-how) at the right place (know-where) and right time (know-when). To name but a few, SMM have been found to underpin optimal performance in soccer and tennis (Gershgoren, Filho, Tenenbaum, & Schinke, 2013; Lausic, Tenenbaum, Eccles, Jeong, & Johnson, 2009), hand-to-hand circus acts (Filho & Rettig, 2019), and medical teams (Westli, Johnsen, Eid, Rasten, & Brattebø, 2010).

Previous research has also shown that teammates working on a task tend to have their psycho-bio-social responses (e.g., heart rate; breathing rate; brain waves and networks) in sync (i.e., locked-in-time), and the higher the level of “sharedness” the higher the synchronization tends to be (Filho, 2019). For instance, members of choir singing teams have been shown to sync their heartbeats during performance (Müller & Lindenberger, 2011), while juggling dyads and duet guitarists have been shown to synchronise their brain-waves during interactive team work (Filho et al., 2016; Sänger, Müller, & Lindenberger, 2012; 2013). Therefore, there is robust neurological evidence that teammates function on similar psycho-bio-social states and share brain rhythms during optimally coordinated interactions. This is relevant because SZOF rests on the notion that “sharedness” can be captured through the monitoring of psycho-bio-social states and patterns and be used to predict and monitor performance in team settings.

Individual Zones of Optimal Functioning

Whereas nomothetic frameworks are about regression to the mean effects (e.g., inverted-U hypothesis), the IZOF framework reflects the notion that individuals possess idiosyncratic psycho-bio-social states underpinning optimal and sub-optimal performance states (Hanin, 2000). Specifically, the *intensity* and *content* of individuals' psycho-bio-social states are theorised to (a) differ in optimal and sub-optimal performance, (b) be expressed through different *forms,* such as communication dynamics and bodily-somatic channels, and (c) be influenced by *time* and *contextual* factors (see the penta-basis of the IZOF framework in Hanin, 2000). Indeed, previous research has revealed that idiosyncratic levels of core affect are more likely to underpin optimal performance (Robazza, Bertollo, Filho, Hanin, & Bortoli, 2016), and that different emotional contents might be more or less functional to performance (Ruiz & Hanin, 2004). Moreover, different individuals manifest their optimal and sub-optimal performance states through unique somatic markers (e.g., heart rate; skin temperature; see Filho, Di Fronso, Mazzoni, Robazza, Bortoli, & Bertollo, 2015), exhibit a range of performance fluctuations over time (Johnson, Edmonds, Moraes, Filho, & Tenenbaum, 2007; Van der Lei, Tenenbaum, & Land, 2016), and show specific IZOF for different performance contexts (Filho, Moraes, & Tenenbaum, 2008).

In practice, the IZOF account has been operationalised through different approaches, including the Individual Affective Probabilistic Zones (IAPZs) method, which estimates a probability of poor, moderate and optimal performance based on an independent variable of interest (e.g., activation; see Kamata, Tenenbaum, & Hanin, 2002; Johnson, Edmonds, Kamata, & Tenenbaum, 2009). Essentially, this probabilistic approach reflects a post-positivist research paradigm, in which the linkage between a predictor variable and an outcome variable do not represent a deterministic function (one-to-one rule), but rather operate under the law of probability (many-to-many basis). To date, researchers and practitioners have used this approach to capture, monitor over time, and design interventions to enhance the probability of optimal performance in competitive situations (see Ruiz, Raglin, & Hanin, 2017).

Overall, the main tenants of the IZOF framework have been validated in general, and through a probabilistic approach in particular, in several empirical studies across sports. Accordingly, scholars and practitioners concur that assessment, intervention and evaluation plans should be idiosyncratic rather than nomothetic and probabilistic rather than deterministic (see Flett, 2015; Hanin, 2000; Ruiz et al., 2017). In the same way, I suggest that teams should have tailored assessments and intervention programs within the SZOF framework, in line with the importance of accounting for within-team idiosyncrasies (Blascovich, Vanman, Mendes, & Dickerson, 2011; Thorson, West, & Mendes, 2018).

Shared Zones of Optimal Functioning

In proposing the SZOF, I have not only blended the SMM and IZOF frameworks as discussed above, but also considered the notion of multi-layered effects in social psychology (Blascovich et al., 2011). Similarly to how Bandura (1997, p. 478) has argued that collective efficacy and self-efficacy have “similar sources, serve similar functions, and operate through similar processes”, I argue that the SZOF is influenced by the same dimensions (intensity, content, time, context, and form; for a review see Hanin, 2000) that influence optimal functioning in individual tasks. Thus, a key difference between the IZOF and the SZOF is the unit of analysis: whereas the IZOF reflects an idea of “I/me” factors, the SZOF is about “We/us” factors. This differentiation is important because team performances and processes are emergent states insofar that they “emerge from the team as a whole rather than from any single individual, akin to the gestalt notion that ‘the whole is greater than the sum of its parts’” (see Filho, 2019, p. 2). To exemplify, an individual might feel confident and perceive his/her performance as optimal for a given team task, whereas the team as a whole might have underperformed and exhibited low collective efficacy throughout the execution of the team task.

Noteworthy, the modelling of emergent states in team settings depends on the phenomenon under investigation. Applied psychologists are interested in myriad phenomenon including compliance, contagion and sharedness and synchrony, to name a few (Thorson et al., 2018). When dealing primarily with sharedness and synchrony, which are of interest in describing optimal functioning in teams, as discussed above, scholars and practitioners should: (a) average individuals' perceptions to derive a team estimate for a given segment of time (e.g., trial; 5-min interval); and (b) consider the relationship between two or more teammates for a given segment of time. Regarding the former, it has been established that averaging processes leads to more reliable estimates when the locus of the study is shared psycho-bio-social states and patterns (Blascovich et al., 2011; Thorson et al., 2018). Regarding the latter, cross-correlating individuals' responses over time allows one to estimate how stable working teams are during the execution of an interactive team task (Thorson et al., 2018). Cross-correlating individuals' responses over time also allows for establishing whether a teammate's psycho-bio-social states predicts other teammate's states, thereby helping to advance understanding of leader-follower dynamics in team settings (Filho, 2019).

It follows that the unique value contribution of the SZOF framework rests on the notion that *sharedness*, *synchrony* and *leader-follower dynamics* underpin optimal functioning and performance fluctuations (i.e., team momentum) at the team level of analysis. That is, to perform optimally, teammates need to be "on the same page", "in sync" over time, and develop functional leadership dynamics. The assessment of performance consistency is also part of the SZOF framework given that the definition of expertise across levels of analyses hinges on the idea of "consistent superior performance" (see Ericsson, Hoffman, Kozbelt, & Williams, 2018). Methodologically, the SZOF aims to capture (a) shared psycho-bio-social states that might underpin optimal functioning in teams; (b) performance fluctuations (team momentum) over time; and (c) *synchrony* during a performance trial or time-window, and *leader-follower dynamics* over time to allow insights in “who leads and who follows” (i.e., leader-follower dichotomy) in a team. In practice, the assessment of sharedness, performance fluctuations, synchrony and leader-follower dynamics can inform interventions aimed at developing high-performing teams; that is, teams consistently performing at the optimal level.

Accordingly, the purposes of this study were to: (a) test the discriminant validity of the SZOF approach by adapting the method proposed by Kamata et al. (2002) to team settings; (b) test whether the SZOF approach would capture idiosyncratic performance fluctuations in teams; and (c) explore whether different teams show idiosyncratic synchrony and leader-follower dynamics during the execution of an interactive task. The respective hypotheses were that different teams would show idiosyncratic SZOF (H1), and idiosyncratic optimal and sub-optimal performance fluctuation patterns (H2). Furthermore, it was expected that different teams would show idiosyncratic leader-follower dynamics (H3).

Methods

Design and Participants

A multi-case study design was used, as the SZOF is grounded on the notion that different teams possess idiosyncratic psycho-bio-social states and patterns linked to optimal and sub-optimal performance experiences. Specifically, three jugglers (1 male and 2 females) participated in the study. Juggler 1 (J1) was 30 years old and the most skilled juggler, with 13 year of experience. Juggler 2 (J2) was 27 years old and had seven years of experience in juggling. Juggler 3 (J3) was 29 years old and had seven years of experience in juggling. To perform the interactive task described next, the jugglers were assembled into three different dyadic teams (i.e., J1-J2; J1-J3; J2-J3). Noteworthy, dyadic juggling has been used as a platform to study shared and complementary psycho-bio-social states because the task is interactive in nature (team performance depends on both teammates) and prevents social loafing (see Filho et al., 2016).

Measures

Arousal and Pleasantness Levels. An adapted version of the affect grid (see Russell, Weiss, & Mendelsohn, 1989) was used. Participants were asked to report on their levels of arousal on a continuum ranging from 1 (sleepiness) to 10 (high arousal). The jugglers also reported on their perceived levels of pleasantness on a continuum ranging from 1 (highly unpleasant) to 10 (pleasant). Of note, previous research supports the notion that core affect, which is a by-product of pleasantness and arousal levels (see Russell et al., 1989), is associated with performance in individual and team tasks (Filho et al., 2016; Robazza et al., 2016).

Attention. The jugglers' perceived level of attention was measured using a 10-point scale ranging from 0 (e.g., task-unrelated, pure dissociation with the task at hand) to 10 (e.g., task-related, pure association with the task at hand). This single-item scale has been used in previous research on the mechanisms of optimal functioning in both individual and team tasks (Basevitch et al., 2011; Filho et al., 2016).

Performance. The objective performance measure was the amount of time juggling, rounded to the nearest second. Specifically, the jugglers were asked to keep the balls in the air for 30 sec or as long as they could, consistent with previous research on cooperative juggling (Berchicci, Quinzi, Dainese, & Di Russo, 2017; Filho et al., 2016; 2017).

Procedures

A circus school in southeast Brazil was contacted via email and a date and time was arranged for data collection. The participants were briefed on the study methodology and signed an informed consent sheet before the commencement of data collection. Each juggling dyad was asked to juggle for 60 trials. In each trial the jugglers were asked to juggle for 30 sec or as long as they could before a ball dropped. Two researchers independently monitored the performance time of each dyad using stopwatches; subsequently, the performance times for each trial were averaged across the researchers. After each trial, each juggler reported his/her levels of arousal, pleasantness, and attention. Importantly, the total number of trials was set based on the central-limit theorem (see Dudley & Dudley, 1999), which purports that 30 data points per participant are usually sufficient to enable the use of the multivariate statistical methods.

Data Analysis

Three analytical procedures were implemented. The first related to the establishment of the SZOF in order to test H1, the second pertained to the use of chi-square analysis to assess performance consistency in order to test H2, and the third involved the use of cross-correlations to estimate within-team synchrony and leader-follower dynamics in order to test H3.

SZOF. A stepwise procedure was used to establish the SZOF. In step 1, averaged scores for all dyads and measures were computed. In step 2, these mean scores per variable and dyad were standardized. In step 3, standardized values above .50 (i.e., half standard-deviation above the mean) were coded as “optimal performance”, whereas values around the mean (-.20 to +.20) were coded as “moderate performance”, and all other negative scores (< -.20) were coded as “poor performance”. This rationale reflects an effect-size based approach to data analysis and is akin to the current standard of report guidelines (see Appelbaum et al., 2018). In step 4, based on the mean values for each variable of interest, poor performances were sub-categorized into poor performances above the optimal zone (PP/A) or poor performances below the optimal zone (PP/B). Similarly, moderate performances were sub-categorized into moderate performances above the optimal zone (MoP/A) or moderate performances below the optimal zone (MoP/B). Of note, this secondary performance categorisation is akin to the notion that poor and moderate performance states might occur below or above optimal performance states (Johnson et al., 2009; Kamata et al., 2002). In step 5, ordinal logistic regression models were conducted (one model per variable and per dyad), resulting in nine SZOF probabilistic curves.

It is important to highlight that the processes of establishing the SZOF are essentially the same of those used to define IAPZs (see Johnson et al., 2009; Kamata et al., 2002). The key difference is that mean scores for a dyad, rather than raw scores for an individual, were used given that the unit of analysis is a team rather than an individual. Again, this is because averaging team processes and performance leads to more reliable estimates when sharedness is the phenomenon under study (Blascovich et al., 2011; Thorson et al., 2018).

Performance consistency. The percentage of optimal performance sequences (i.e., two or more optimal performances in subsequent trials) and poor performance sequences (i.e., two or more poor performances in subsequent trials) was computed for each dyad and with respect to the total number of trials. Chi-square tests were used to assess whether the frequency distribution of these sequences across dyads was statistically significant.

Within-Team Synchrony and leader-follower dynamics. Cross-correlational analysis is a statistical function used to estimate the relationship between two-time series (Box, Jenkins, Reinsel, & Ljung, 2015). In the present study, cross-correlations were computed based on each individual’s raw scores for arousal, pleasantness, and attention according to each dyad combination and across the 60 performance trials. A five-lag period was used to compute each cross-correlation, and thereby to estimate (a) *synchrony* as the correlation between the jugglers perceived states during the same trial, i.e., “lag 0"; and (b) *leader-follower dynamics* within each dyad by establishing whether a juggler’s arousal, pleasantness or attentional states predicted the other juggler's perceived states within a 5-trial interval. Accordingly, nine cross-correlation graphs (one per variable and per dyad) were generated.

Results

Discriminant Validity of the SZOF Framework

The range and probability of all computed SZOF are presented in Table 1. SZOF probabilistic curves for arousal, pleasantness, and attention are shown in Figures 1, 2 and 3. To serve as a baseline for comparison with the SZOF, the jugglers' IZOF were computed and are also presented in Figures 1, 2 and 3. Each jugglers' IZOF was based on the performance scores for the dyad as a whole, as a solo juggling task was not part of the study. Noteworthy, it was not possible to establish a SZOF for attention for the dyad J2-J3, probably because these novice jugglers experienced cognitive overload and did not know how to regulate their attentional focus (i.e., where to gaze at and for how long), as often happens with novice performers (i.e., *target control strategy*; see Tenenbaum & Filho, 2017). Overall, from the aforementioned table and figures, it is evident that each dyad showed (a) idiosyncratic probabilities of optimal and sub-optimal performance for each one of the variables of interest, and (b) different ranges for their SZOF. Furthermore, inspection of Figure 1 also suggests that (a) the jugglers' IZOF differ from their SZOF attesting to the discriminant validity between these two frameworks, and (b) the IZOF for each variable of interest (arousal, pleasantness, and attention) changes for all jugglers, but relatively less for J1, the more experienced juggler in comparison to J2 and J3. Together, these results support H1 and attest that the SZOF framework captures idiosyncratic patterns of poor, moderate, and optimal performance in dyadic teams

Capturing Performance Fluctuations within the SZOF Framework

The percentage of optimal and poor performances were computed for each dyad. Inferential analysis of these frequencies revealed that the dyads differed in their distribution of poor performance sequences; however, no statistical difference across dyads for the optimal performance sequences was observed (Table 2). Overall, these findings lend support to H2, which purported that optimal and sub-optimal performance fluctuation patterns would differ across dyads.

Within-Team Synchrony and Leader-Follower Dynamics

The pattern of significant cross-lag correlations for arousal differed slightly across the dyads, as illustrated in Figure 4. Correlations at lag 0 were similar across dyads; $r = .35$ for J1-J2, $r = .32$ for J1-J3, and $r = .30$ for J2-J3. These findings suggest that, within each dyadic team, the jugglers' levels of arousal co-varied positively and to a small-to-moderate magnitude during the same given trial. No significant correlations at all other lag periods were observed for J1-J2 and for J1-J3. However, for J2-J3 a significant correlation was observed at lag -5 ($r = -.30$), suggesting that a decrease in perceived arousal in J2 resulted in an increase in J3's arousal in the subsequent trial. Hence, J2's arousal levels could be used to predict J3's arousal levels for a five-trial window difference.

The pattern of cross-lag correlations for pleasantness differed across dyads, as illustrated in Figure 5. First, J1-J2 pleasantness responses correlated significantly at lag 0 ($r = .57$), lag -1 ($r = -.34$), and lag 1 ($r = -.48$), thus suggesting that (a) their pleasantness states co-varied positively during the same given trial, (b) decreases in pleasantness in either juggler led to an increase in pleasantness in the other juggler for the subsequent trial, and (c) J2's pleasantness states had a slightly greater influence (or predictive power) in the dyad pleasantness for the subsequent trial. Second, J1-J3 pleasantness responses correlated significantly at lag 0 ($r = .57$) and lag 1 ($r = -.48$), thus suggesting that their pleasantness states co-varied in the same direction for the same trial, and that a decrease in J2's pleasantness states led to a decrease in J1's pleasantness states in the next trial. Thus, one could use J2's ("the leader") pleasantness states to predict J1's ("the follower") pleasantness states for the next trial. Finally, J2-J3 pleasantness states did not correlate over time, thus suggesting that they were independent of one another and that co-regulation of this affective dimension did not occur throughout the juggling task.

The pattern of cross-lag correlations for attentional states differed greatly across dyads, as illustrated in Figure 6. For J1-J2, perceived attention responses correlated significantly at lag 0 (r = .44), lag -1 (r = -.30), and lag 1 (r = -.43), thus suggesting that (a) their attentional states co-varied positively during the same given trial, (b) decreases in attentional states in either juggler led to an increase in attentional states in the other juggler for the subsequent trial, and (c) J2's attentional states had a slightly greater influence in their shared levels of attention for the subsequent trail. For J1-J3, cross-lag correlations were significant at lag 0 (r = .48), lag -3 (r = -.26), lag 1 (r = -.40), and lag 5 (r = -.35), suggesting that (a) their attentional states co-varied positively during the same given trial, (b) an increase in J1's attentional states resulted in a decrease in J3's attentional states three trials later, and (c) an increase in J3's attentional states led to a decrease in J1's attentional state five trials later and in the immediately subsequent trial. Thus, J1 and J3 engaged in co-regulation of their attentional states, with both jugglers' attentional states being predictive of the other over time, but with J3's attentional states being more predictive of J1's states overall. Finally, J2-J3's cross-correlation patterns were significant at lag 0 (r = .37) and lag -1 (r = -.32), thus suggesting that their attentional states co-varied positively for the same given trial, and that a decrease in J2's attentional states led to a decrease in J3's attentional states in the subsequent trial; in other words, one could use J2's attentional states to predict J3's attentional states on a trial-to-trial basis.

Altogether, these findings lend support to H3 because they revealed that different dyads have idiosyncratic synchrony dynamics for a given trial or specific time-window, and leader-follower dichotomy patterns, with respect to arousal, pleasantness and attention. That is, within different dyads different co-regulation patterns emerged for the different variables of interest, and different jugglers had greater influence, thus acting more of “a leader” than a “follower” in the affective or attentional response of the other.

More specifically, within the different dyads idiosyncratic *shared leadership* and *leader-follower dichotomy* dynamics emerged. *Shared leadership*, which reflected a co-regulation mechanism, took place when the jugglers had similar influence on one another’s affective and attentional states during a given performance trial (lag 0) and over time (i.e., lags – 1 to – 5, and lags 1 to 5). *Leader-follower dichotomy* occurred when one juggler had greater influence within the dyad, thus acting more of a leader than a follower, in the affective or attentional response of the other. The instances where a clear leader-follower pattern emerged likely reflect a *reciprocal compensation mechanism*, as one juggler influences the direction of the system towards an optimum balance. To this extent, outside of lag 0, all significant correlations were negative, indicating that an increase in one juggler’s affective or attentional states led to a decrease in the other juggler’s affective or attentional states, likely to maintain an optimal level of core affect or joint attention to ensure the completion of the interactive juggling task.

Discussion

In the present study, the hypotheses that different teams would show idiosyncratic SZOF (H1), optimal and sub-optimal performance fluctuation patterns (H2), and within-team synchrony and leader-follower dynamics (H3) were tested and verified. The theoretical, methodological and applied implications of these findings are elaborated upon next.

Discriminant Validity of the SZOF Framework

The three dyadic teams showed different SZOF for arousal, pleasantness and attention, with respect to the location, range and probability of their optimal, moderate and poor performance zones. As such, the conceptual framework proposed herein has been shown to capture and discriminate idiosyncratic patterns underpinning optimal and sub-optimal performance in different teams. Theoretically, these findings align with the seminal IZOF framework (Hanin, 2000), which purported that intra-group dynamics contribute to optimal and sub-optimal performance experiences in team settings. Also, comparison of the jugglers' SZOF with their idiosyncratic IZOF revealed that the levels of arousal, pleasantness and attention required to perform optimally in individual and team settings differed. These differences between the jugglers' IZOF and SZOF highlights that the mechanisms behind optimal functioning in individuals and teams differ, congruent with the gestalt notion that "the whole is greater than the sum of the parts".

Methodologically, it is important to reiterate that the SZOF proposal is an adaptation of the probabilistic approach proposed by Kamata et al. (2002), which validity has been attested in several studies across different samples (e.g., Flett, 2015; Johnson et al., 2009; Robazza et al., 2016; Van der Lei et al., 2016). In adapting Kamata et al.'s methodology to team settings, I have used standardized scores to create poor, moderate, and optimal performance zones for teams. I argue that the use of standardized performance scores is more appropriate than the use of median-split techniques, because for some performers optimal performance is not performance above the mean but rather exceptional performance (e.g., above the 90th percentile; see Bortoli, Bertollo, Hanin, & Robazza, 2012). Accordingly, I suggest that the criteria to establish optimal, moderate, and poor performance levels should be tailored to the team and the context of interest.

Capturing Performance Fluctuations within the SZOF Framework

The establishment of the SZOF allowed for a frequency count analysis of optimal and poor performance sequences across teams. While the teams did not differ in their distribution of optimal performance sequences, they were found to differ in the distribution of their poor performance sequences. Generally, these findings support the claim that individuals and teams have idiosyncratic in-and-out of the zone performance fluctuation patterns (Filho et al., 2008; Robazza et al., 2016). More specifically, these findings suggest that the SZOF framework and methodology can be used as a platform to capture performance fluctuations in teams.

Furthermore, these findings suggest that both optimal and poor performance sequences merit attention, as teams want to avoid bad momentum (sequences of poor performance), while enhancing their chances of experiencing good momentum (sequences of optimal performance) during competitive situations (Filho et al., 2008; Hanin, 2000). Although most existing research has focused on optimum performance sequences, scholars and practitioners should not overlook the implications of poor performance sequences in team settings. To this extent, accidents in civil aviation and sports tend to occur due to a sequence of poor performances, which iterative effects often lead to a team coordination breakdown (Van Fenema, 2005; Wergin, Zimanyi, Mesagno, & Beckmann, 2018). Importantly, findings of the present study also suggest that the key to increasing good team momentum is linked to leader-follower dynamics and the development of within-team affective and attentional synchrony.

Within-Team Synchrony and Leader-Follower Dynamics

Cross-correlational analysis suggests that the different teams showed singular synchrony patterns pertaining to arousal, pleasantness and attention. In other words, for a given performance trial, the degree of association between the two jugglers' arousal, pleasantness and attentional states differed. To this extent, previous research suggests that teammates must exhibit a degree of synchrony to perform satisfactorily in an interactive motor task (Filho et al., 2016; 2017; Sänger, Müller, & Lindenberger, 2012; 2013). Specifically, the correlation patterns observed at lag 0 for all jugglers and variables of interest support the SZOF framework proposed herein, which purports that different teams possess idiosyncratic synchrony patterns linked to optimal and sub-optimal performance.

The findings also revealed that each dyad showed unique leader-follower dynamics regarding arousal, pleasantness, and attention. While it was possible to identify a leader and a follower within the dyads for arousal (e.g., J2-J3), pleasantness (i.e., J1-J3) and attentional states (i.e., J1-J3, and J2-J3), it was also evident that the jugglers engaged in shared-leadership for arousal regulation (i.e., J1-J2; J1-J3) and that J1 and J2 exerted more similar than dissimilar levels of leadership on each other's pleasantness and attentional levels. Together, these findings corroborate the notion that specific individuals might lead different aspects of team functioning, but other aspects of team functioning are regulated through a shared-leadership process (for a review see Cotterill & Fransen, 2016).

In light of these findings, I reiterate that *co-regulation* is a sub-process of *shared-leadership*, whereas *reciprocal compensation* occurs when a clear leader-follower dichotomy emerges within the team; that is, *if* there is a leader *then* the leader tries to influence the follower and the balance of the system as a whole towards an optimal state. Indeed, *co-regulation* refers to the mutual regulation of team functioning, whereas *reciprocal compensation* occurs when one teammate adapts and responds to changes in other teammates in order to improve team functioning (Filho, 2019). In other words, within the same team shared-leadership and leader-follower dynamics coexist, and thereby teams engage in both *co-regulation* and *reciprocal compensation* strategies to reach and sustain a shared affective and attentional state (SZOF) linked to optimal performance.

Theoretical and Applied Implications

In theory, the findings of this study help to evolve the notion of SZOF. Based on the insights gained from the deductive thinking informing the study, and the inductive insights emerging from the data itself, I suggest that the five IZOF dimensions are *formative* of the SZOF framework. It is the optimal combination among each individual's psycho-bio-social states and patterns (I/me processes), which are influenced by five dimensions as discussed by Hanin (2000), that results in the emergence of an optimal team functioning (We/us processes), herein denoted as SZOF. In turn, these SZOF are underpinned by at least three measurable (manifest variables) reflective indicators, namely *synchrony*, *leadership dynamics*, and *team momentum* (Figure 7). Thus, the SZOF framework offers a theoretical and applied platform to objectively measure the degree of synchrony, the direction of leadership (who leads and who follows), and momentum performance fluctuations within teams. More specifically, synchrony pertains to the co-variance among teammates' psycho-bio-social states before, during and after performance events. Leadership dynamics is manifested through the prevalence of shared-leadership and leader-follower dichotomy patterns, wherein teammates either co-regulate team processes or reciprocally compensate for one another in order to reach and sustain optimal functioning. Finally, team momentum pertains to measurable sequences of poor or optimal performance.

In practice, findings from this study can be used to establish SZOF for dyadic teams, to monitor their performance fluctuations over time, and to identify patterns of shared-leadership, and leader-follower dichotomy. Scholars and practitioners can use mental skills training, group dynamics exercises, and team-level bio-neuro-feedback interventions to help teammates to learn how to co-regulate and reciprocally compensate for one another in order to broaden their SZOF, increase their probability of optimal performance, and reach and sustain optimal performance over time. Indeed, all dyads in the present study could benefit from a tailored intervention as their probabilities of optimal performance were generally low

(≤ 40%), perhaps because J2 and J3 were novices and the dyads did not practice together regularly. Furthermore, the SZOF can be used to match different individuals to assemble high-performing teams. For instance, different individuals can go through a training and familiarization period together, then have their SZOF established, which in turn can be used to estimate best-fit combinations of dyadic teams. Practitioners can also apply the SZOF principles to sub-teams, such as to a goalkeeper and defender that often interact within a larger soccer team, or a midfielder and striker that must combine passes to score a goal.

Overall, the SZOF framework offers a platform to study and develop interventions for dyadic teams and sub-teams, and potentially triadic and larger teams as discussed below. There are several dyadic team sports, including badminton, beach volleyball, diving, motorsports, and tennis. Beyond sports, civil and military aviation, music duets, and performance artists can be studied through the SZOF framework and methodology. Research on creativity has shown that dyadic teams produce some of the best outputs in music, arts, and science (Shenk, 2014). The approach proposed herein can help to advance understanding of the mechanisms that explain not only peak performance but also creative endeavours in team settings.

Limitations and Future Research

First, as discussed throughout, previous research suggests that optimal team functioning is partly due to psycho-bio-social synchronisation. Accordingly, the lack of multiple data sources is a limitation of this study, especially given that triangulation of different data sources is recommended to prevent common method bias (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). As such, scholars should pursue multimodal assessments in future research and aim to collect both subjective and objective psycho-bio-social processes and performance data. Second, in the present study the three participants were combined into different teams. While such a controlled arrangement allowed the researcher to observe how the interaction between different individuals led to the establishment of different SZOF, the study of “real-world teams” is needed to corroborate the SZOF. Third, this study did not have an individual (control) condition and thus the IZOF reported here were based on the performance scores for the dyad as a whole rather on the scores of each individual. Future studies should include an individual (control) condition, as discussed in detail elsewhere (Filho, Bertollo, Robazza, & Comani, 2015).

Additional research on how team tenure and skill-level differences between teammates might influence the establishment of SZOF is particularly warranted. The study of same gender and mixed-gender dyads is important to understand gender effects within the SZOF framework. The study of multi-cultural and cross-cultural teams through the SZOF lens is also important in an increasingly diverse and globalized world.

Another area for future research includes the study of larger teams. Specifically, it is important to explore whether the reliability of the SZOF framework holds true to the study of larger teams (n > 2), especially given that variance increases with more degrees of freedom and team size is implicated in performance across the natural world (Dunbar, 1993). Again, research on sub-teams is also warranted, particularly the study of duos that seem to be essential to overall team performance. To this point, the duo of Lionel Messi and Luis Suárez scored over 63% of the goals for soccer powerhouse Barcelona in the 2018-19 Spanish League season (see https://www.foxsports.com/soccer/stats), and John Lennon ad Paul McCartney composed the majority of the Beatles songs. Hence, establishing the SZOF of key sub-teams might be relevant to practitioners.

The theoretical ideas proposed herein should be explored through advanced neuro-scientific and statistical methods. Regarding the former, the study of hyper-brain couplings, such as whether brain synchrony across frequency ranges (e.g., alpha, beta, theta) is implicated in optimal and sub-optimal performance in team settings, is warranted. Regarding the latter, the SZOF (Figure 7) offers a conceptual framework to explore cross-level interactions among individual and team factors. Thus, multi-level modelling can be used in future research to examine peak performance in large nested datasets, as such a statistical approach captures both regression to the mean effects (between-individuals and between-teams) and within-subject and within-team variability patterns (Hoyle, 2011). More generally, research on different sports and performance fields (e.g., aviation, music) are needed to verify whether the SZOF framework is instrumental in capturing peak performance, and estimating within-team performance fluctuations, synchrony and leader-follower dynamics.

References

Appelbaum, M., Cooper, H., Kline, R. B., Mayo-Wilson, E., Nezu, A. M., & Rao, S. M. (2018). Journal article reporting standards for quantitative research in psychology: The APA Publications and Communications Board task force report. *American Psychologist*, *73*(1), 3-25. doi: 10.1037/amp0000191

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York, NY: W.H. Freeman.

Basevitch, I., Thompson, B., Braun, R., Razon, S., Arsal, G., Tokac, U., Filho, E., Nascimento, T., & Tenenbaum, G. (2011). Olfactory effects on attention allocation and perception of exertion. *The Sport Psychologist*, *25*(2), 144-158. doi: 10.1123/tsp.25.2.144.

Berchicci, M., Quinzi, F., Dainese, A., & Di Russo, F. (2017). Time-source of neural plasticity in complex bimanual coordinative tasks: Juggling. *Behavioural brain research*, *328*, 87-94. doi: 10.1016/j.bbr.2017.04.011

Blascovich, J., Vanman, E., Mendes, W. B., & Dickerson, S. (2011). *Social psychophysiology for social and personality psychology*. Thousand Oaks, CA: Sage Publications.

Bortoli, L., Bertollo, M., Hanin, Y., & Robazza, C. (2012). Striving for excellence: A multi-action plan intervention model for shooters. *Psychology of Sport and Exercise*, *13*(5), 693-701. doi: 10.1016/j.psychsport.2012.04.006

Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: forecasting and control*. Hoboken, NJ: John Wiley & Sons.

Cotterill, S. T., & Fransen, K. (2016). Athlete leadership in sport teams: Current understanding and future directions. *International Review of Sport and Exercise Psychology*, *9*(1), 116-133. doi: 10.1080/1750984X.2015.1124443

Dudley, R. M., & Dudley, R. M. (1999). *Uniform central limit theorems* (No. 63). Cambridge, United Kingdom: Cambridge University Press.

Dunbar, R. I. (1993). Coevolution of neocortical size, group size and language in humans. *Behavioral and Brain Sciences, 16*, 681-694. doi: 10.1017/S0140525X00032325

Ericsson, K. A., Hoffman, R. R., Kozbelt, A., & Williams, A. M. (Eds.). (2018). *The Cambridge handbook of expertise and expert performance*. Cambridge, United Kingdom: Cambridge University Press.

Filho, E. (2019). Team dynamics theory: Nomological network among cohesion, team mental models, coordination, and collective efficacy. *Sport Sciences for Health*, *15*(1), 1-20. doi: 10.1007/s11332-018-0519-1

Filho, E., Bertollo, M., Robazza, C., & Comani, S. (2015). The juggling paradigm: a novel social neuroscience approach to identify neuropsychophysiological markers of team mental models. *Frontiers in Psychology,* 1-6.

Filho, E., Bertollo, M., Tamburro, G., Schinaia, L., Chatel-Goldman, J., di Fronso, S., … Comani, S. (2016). Hyperbrain features of team mental models within a juggling paradigm: A proof of concept. *PeerJ*, 1-38.

Filho, E., Di Fronso, S., Mazzoni, C., Robazza, C., Bortoli, L., & Bertollo, M. (2015). My heart is racing! Psychophysiological dynamics of skilled racecar drivers. *Journal of Sports Sciences*, *33*, 945-959. doi: 10.1080/02640414.2014.977940

Filho, E., Moraes, L. C., & Tenenbaum, G. (2008). Affective and physiological states during archery competitions: Adopting and enhancing the probabilistic methodology of individual affect-related performance zones (IAPZs). *Journal of Applied Sport Psychology*, *20*, 441-456. doi: 10.1080/10413200802245221

Filho, E., Pierini, D., Robazza, C., Tenenbaum, G., & Bertollo, M. (2017). Shared mental models and intra-team psychophysiological patterns: A test of the juggling paradigm. *Journal of Sports Sciences*, *35*(2), 112-123. doi: 10.1080/02640414.2016.1158413

Filho, E., & Rettig, J. (2019). Team coordination in high-risk circus acrobatics. *Interaction Studies*, *19*, 501-520. doi: 10.1075/is.16035.fil

Filho, E., & Tenenbaum, G. (2012). Team mental models in sports: An overview. In R. Schinke (Ed.), *Athletic insight's writings in sport psychology* (pp. 329-342). Hauppauge, NY: Nova Science Publishers, Inc.

Flett, M. R. (2015). Creating probabilistic idiographic performance profiles from discrete feelings: Combining the IZOF and IAPZ models. *Sport Science Review*, *24*, 241-266. doi: 10.1515/ssr-2015-0018

Fox Sports (2019). Retrieved on July 11, 2019. https://www.foxsports.com/soccer/stats?competition=2&category=standard&sort=3

Gershgoren, L., Filho, E., Tenenbaum, G., & Schinke, R. J. (2013). Coaching shared mental models in soccer: A longitudinal case study. *Journal of Clinical Sport Psychology*, *7*, 293-312. doi: 10.1123/jcsp.7.4.293

Hackman, J. R., & Wageman, R. (2005). A theory of team coaching. *Academy of Management Review*, *30*, 269-287. doi: 10.5465/amr.2005.16387885

Hanin, Y. L. (Ed.). (2000). Emotions in sport. Champaign, Illinois: Human Kinetics.

Hoyle, R. H. (2011). *Structural equation modeling for social and personality psychology*. Thousand Oaks, CA: Sage Publications.

Johnson, M. B., Edmonds, W. A., Kamata, A., & Tenenbaum, G. (2009). Determining individual affect-related performance zones (IAPZ): A tutorial. *Journal of Clinical Sports Psychology, 3,* 34-57. doi: 10.1123/jcsp.3.1.34

Johnson, M. B., Edmonds, W. A., Moraes, L. C., Filho, E. S., & Tenenbaum, G. (2007). Linking affect and performance of an international level archer incorporating an idiosyncratic probabilistic method. *Psychology of Sport and Exercise*, *8*(3), 317-335. doi: 10.1016/j.psychsport.2006.05.004

Kamata, A., Tenenbaum, G., & Hanin, Y. L. (2002). Individual zone of optimal functioning (IZOF): a probabilistic estimation. *Journal of Sport & Exercise Psychology*, *24*, 189-208. doi: 10.1123/jsep.24.2.189

Lausic, D., Tenenbaum, G., Eccles, D., Jeong, A., & Johnson, T. (2009). Intrateam communication and performance in doubles tennis. *Research Quarterly for Exercise & Sport*, *80*(2), 281-290. doi: 10.1080/02701367.2009.10599563

Lim, B. C., & Klein, K. J. (2006). Team mental models and team performance: A field study of the effects of team mental model similarity and accuracy. Journal of Organizational Behavior, 27, 403-418.

Mohammed, S., Ferzandi, L., & Hamilton, K. (2010). Metaphor no more: A 15-year review of the team mental model construct. *Journal of Management*, *36*, 876-910. doi: 10.1177/0149206309356804

Müller, V., & Lindenberger, U. (2011). Cardiac and respiratory patterns synchronize between persons during choir singing. *PloS ONE*, *6*, e24893.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-903. doi: 10.1037/0021-9010.88.5.879

Popper, K. (2005). *The logic of scientific discovery*. New York, NY: Routledge.

Robazza, C., Bertollo, M., Filho, E., Hanin, Y., & Bortoli, L. (2016). Perceived control and hedonic tone dynamics during performance in elite shooters. *Research Quarterly for Exercise and Sport*, *87*(3), 284-294. doi: 10.1080/02701367.2016.1185081

Ruiz, M., & Hanin, Y. (2004). Metaphoric description and individualized emotion profiling of performance states in top karate athletes. *Journal of Applied Sport Psychology*, *16*, 258-273. doi: 10.1080/10413200490498366

Ruiz, M. C., Raglin, J. S., & Hanin, Y. L. (2017). The individual zones of optimal functioning (IZOF) model (1978–2014): Historical overview of its development and use. *International Journal of Sport and Exercise Psychology*, *15*(1), 41-63. doi: 10.1080/1612197X.2015.1041545

Russell, J. A., Weiss, A., & Mendelsohn, G. A. (1989). Affect grid: A single-item scale of pleasure and arousal. *Journal of Personality & Social Psychology*, *57*(3), 493-502. doi: 10.1037/0022-3514.57.3.493

Sänger, J., Müller, V., & Lindenberger, U. (2012). Intra- and interbrain synchronization and network properties when playing guitar in duets. *Frontiers in Human Neuroscience*, *6*, 1-19. doi: 10.3389/fnhum.2012.00312

Sänger, J., Müller, V., & Lindenberger, U. (2013). Directionality in hyperbrain networks discriminates between leaders and followers in guitar duets. *Frontiers in Human Neuroscience*, *7*, 1-14. doi: 10.3389/fnhum.2013.00234

Shenk, J. W. (2014). *Powers of two: Finding the essence of innovation in creative pairs*. Boston, MA: Houghton Mifflin Harcourt.

Tenenbaum, G., & Filho, E. (2017). Decision-making in sports: A cognitive and neural basis perspective. *Reference module in neuroscience and biobehavioral psychology*. Philadelphia, PA: Elsevier.

Thorson, K. R., West, T. V., & Mendes, W. B. (2018). Measuring physiological influence in dyads: A guide to designing, implementing, and analyzing dyadic physiological studies. *Psychological Methods*, *23*(4), 595-616. doi: 10.1037/met0000166

Van der Lei, H., Tenenbaum, G., Land, W. M. (2016). Individual arousal-related performance zones effect on temporal and behavioral patterns in golf routines. *Psychology of Sport and Exercise, 26,* 52-60. doi: 10.1016/j.psychsport.2016.06.005

Van Fenema, P. C. (2005). Collaborative elasticity and breakdowns in high reliability organizations: Contributions from distributed cognition and collective mind theory. *Cognition, Technology & Work, 7*(2), 134-140. doi: 10.1007/s10111-005-0181-7

Wergin, V. V., Zimanyi, Z., Mesagno, C., & Beckmann, J. (2018). When suddenly nothing works anymore within a team–Causes of collective sport team collapse. *Frontiers in Psychology, 9*, 2115. doi: 10.3389/fpsyg.2018.02115

Westli, H., Johnsen, B., Eid, J., Rasten, I., & Brattebø, G. (2010). Teamwork skills, shared mental models, and performance in simulated trauma teams: An independent group design. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine, 18,* 1-8.

Table 1

Range and Probability of Optimal Performance per Dyad for the Arousal, Pleasantness and Attention SZOF

Dyad	Arousal		Pleasantness		Attention	
	Range	Probability	Range	Probability	Range	Probability
J1-J2	6.00-8.45	.35	5.18-7.09	.43	6.0-7.73	.48
J1-J3	6.91-8.27	.39	5.64-10.00	.28	6.18-8.64	.46
J2-J3	8.36-8.91	.42	6.91-8.00	.34	-	-

Table 2

Percentage of Optimal and Poor Performance Sequences per Dyad

Performance Sequences	Dyad			χ^2
	J1-J2	J1-J3	J2-J3	
Optimal	15.00	10.00	10.00	.71; p = .40
Poor	10.00	16.66	27.00	8.11; p = .02

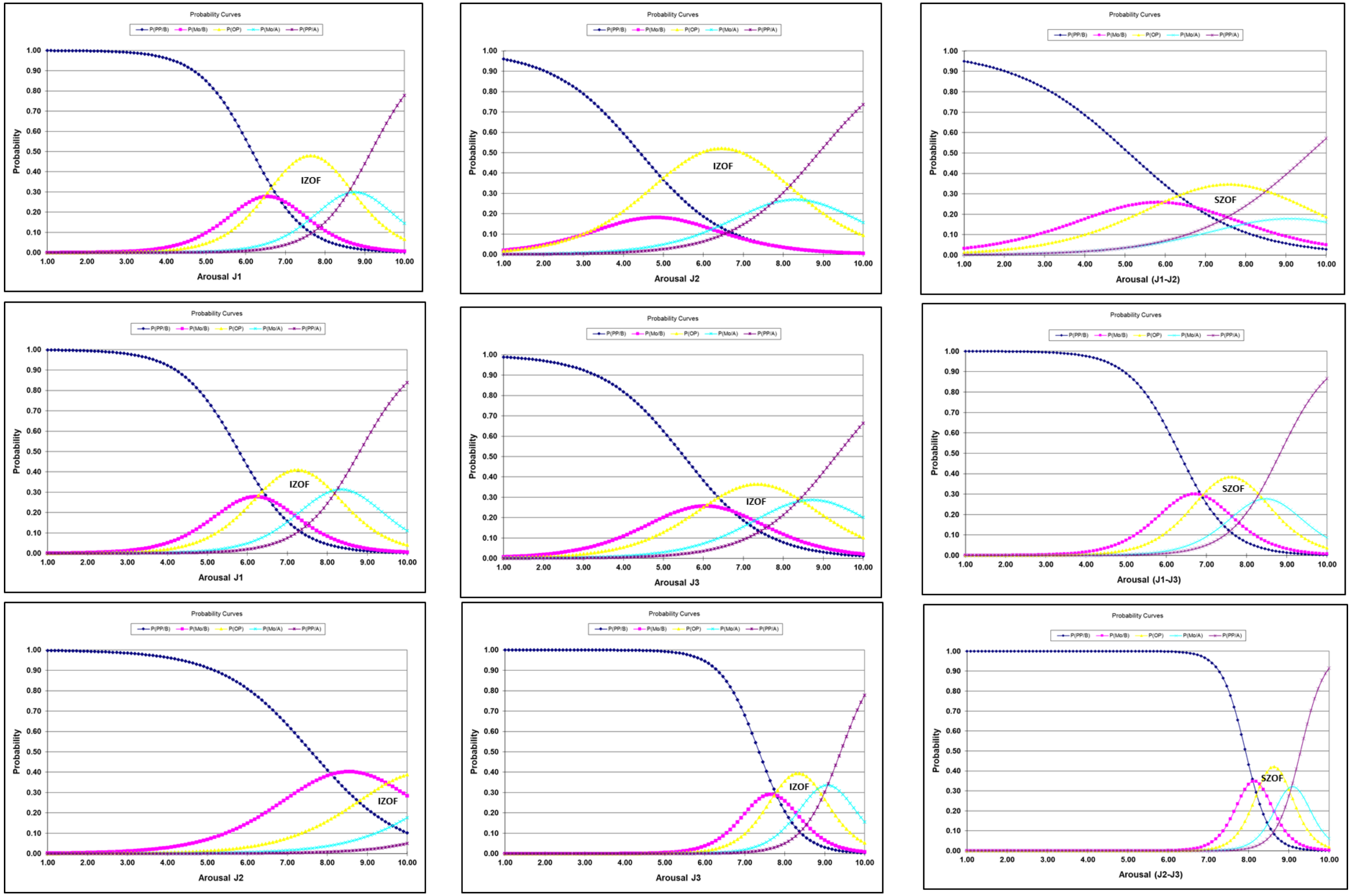

Figure 1. SZOF probabilistic curves for pleasantness levels for the J1-J2 (upper panel), J1-J3 (middle panel) and J2-J3 (lower panel) dyadic teams. *Note.* P(PP/B) stands for Probability of Poor Performance Below the Optimal Zone. P(Mo/B) stands for Probability of Moderate Performance Below the Optimal Zone. P(OP) stands for Probability of Optimal Performance. P(Mo/A) stands for probability of Moderate Performance Above the Optimal Zone. P(PP/A) stands for Probability of Poor Performance Above the Optimal Zone.

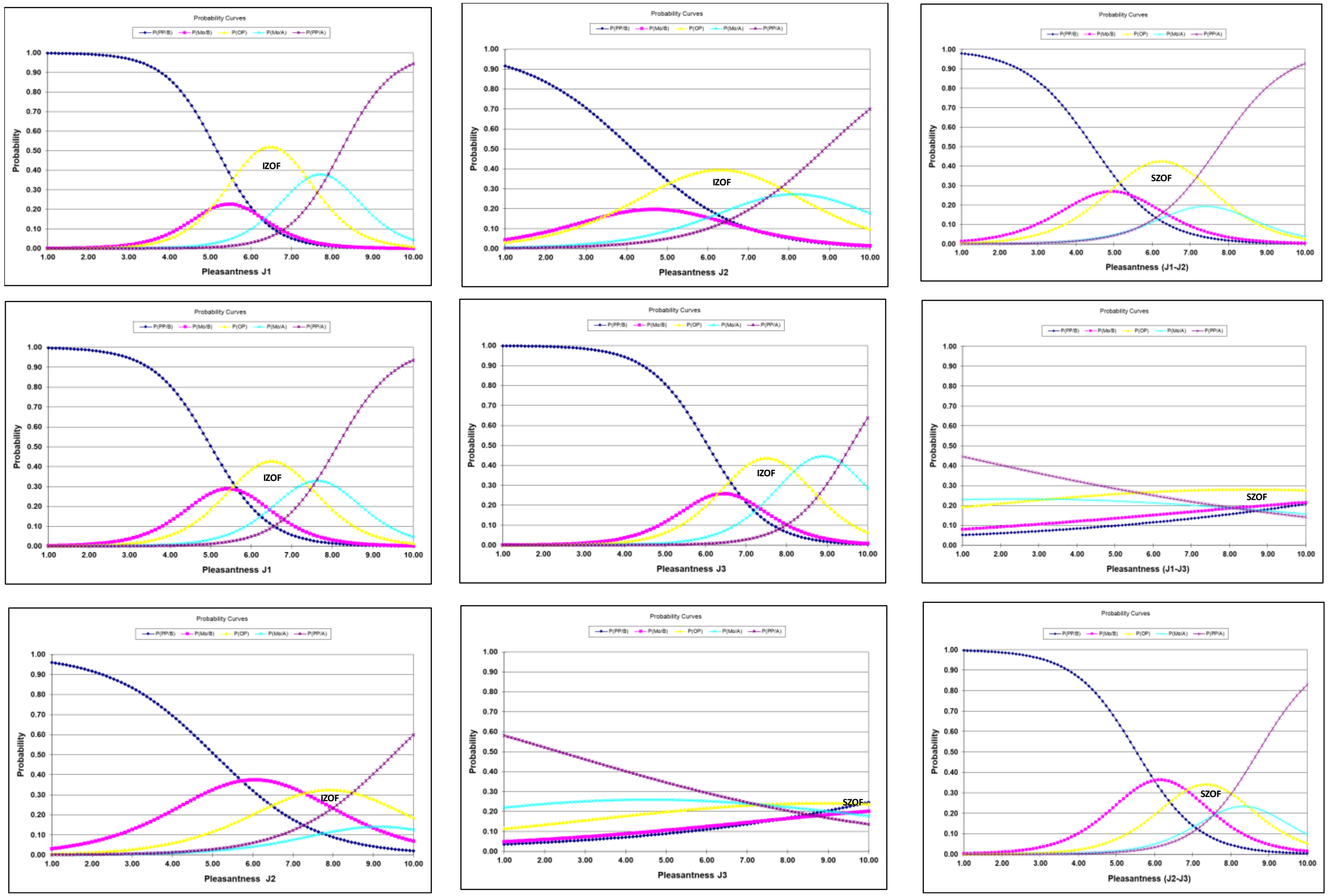

Figure 2. SZOF probabilistic curves for pleasantness levels for the J1-J2 (upper panel), J1-J3 (middle panel) and J2-J3 (lower panel) dyadic teams. *Note.* P(PP/B) stands for Probability of Poor Performance Below the Optimal Zone. P(Mo/B) stands for Probability of Moderate Performance Below the Optimal Zone. P(OP) stands for Probability of Optimal Performance. P(Mo/A) stands for probability of Moderate Performance Above the Optimal Zone. P(PP/A) stands for Probability of Poor Performance Above the Optimal Zone.

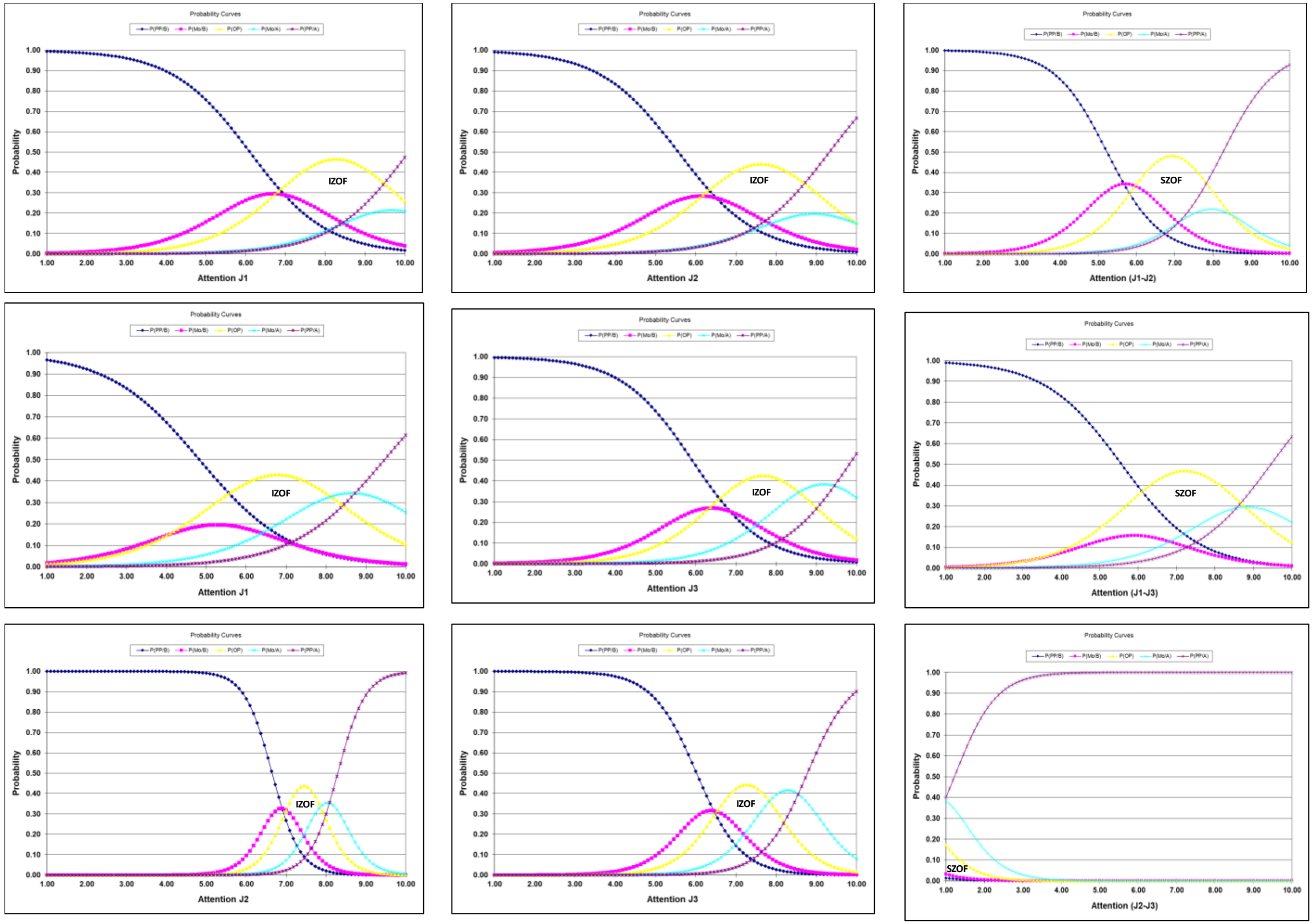

Figure 3. SZOF probabilistic curves for attentional levels for the J1-J2 (upper panel), J1-J3 (middle panel) and J2-J3 (lower panel) dyadic teams.
Note. P(PP/B) stands for Probability of Poor Performance Below the Optimal Zone. P(Mo/B) stands for Probability of Moderate Performance Below the Optimal Zone. P(OP) stands for Probability of Optimal Performance. P(Mo/A) stands for probability of Moderate Performance Above the Optimal Zone. P(PP/A) stands for Probability of Poor Performance Above the Optimal Zone.

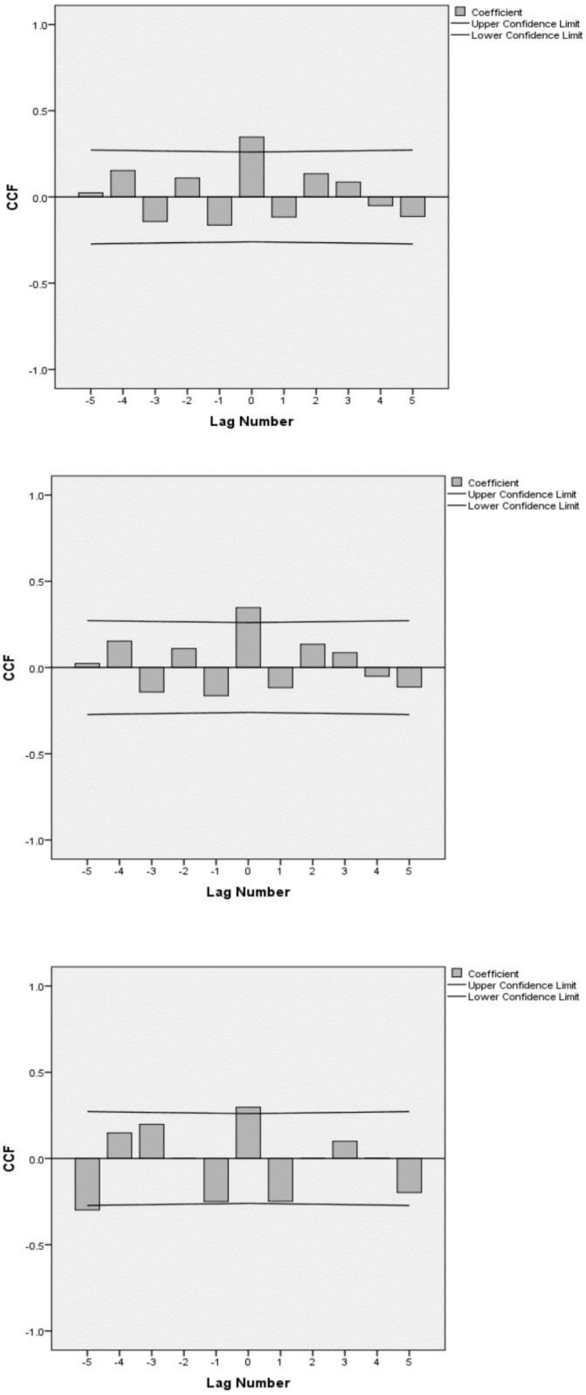

Figure 4. Cross-correlation coefficients for arousal levels for the J1-J2 (upper panel), J1-J3 (middle panel) and J2-J3 (lower panel) dyadic teams.

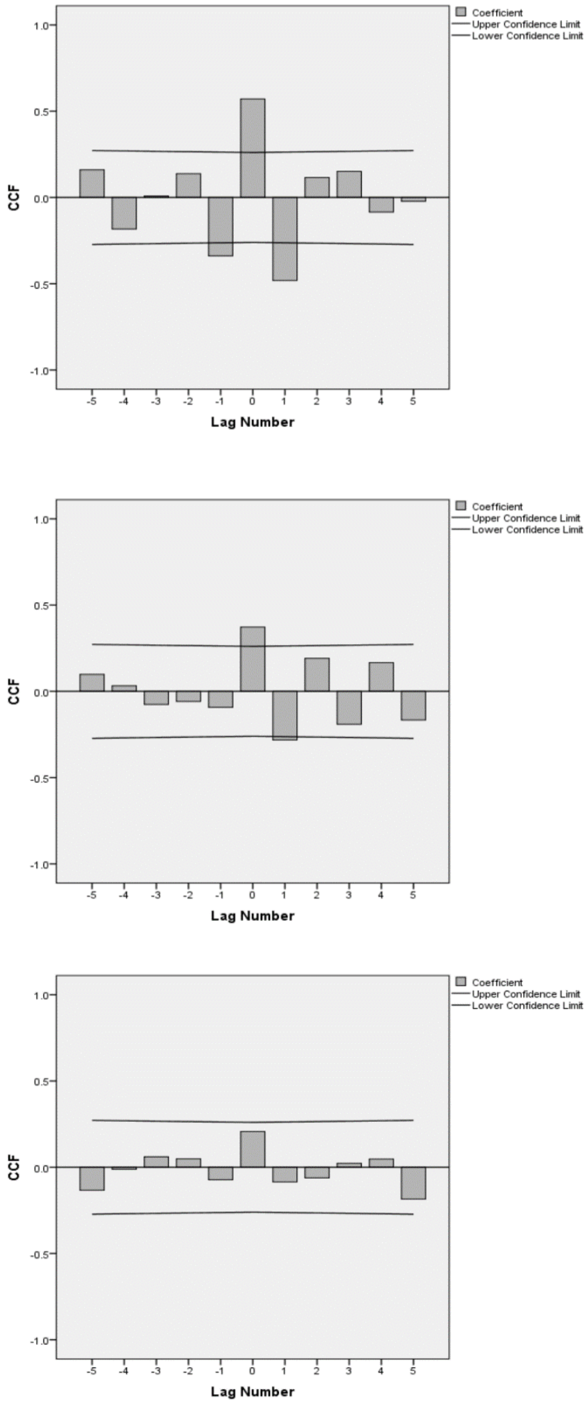

Figure 5. Cross-correlation coefficients for pleasantness levels for the J1-J2 (upper panel), J1-J3 (middle panel) and J2-J3 (lower panel) dyadic teams.

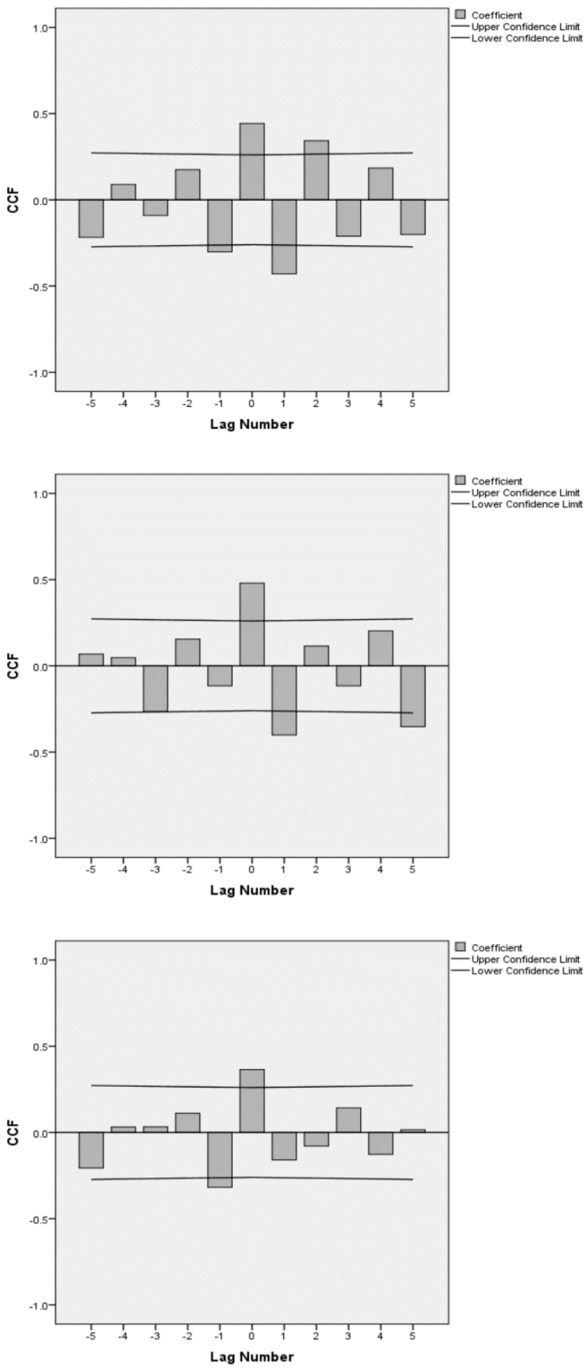

Figure 6. Cross-correlation coefficients for attentional levels for the J1-J2 (upper panel), J1-J3 (middle panel) and J2-J3 (lower panel) dyadic teams.

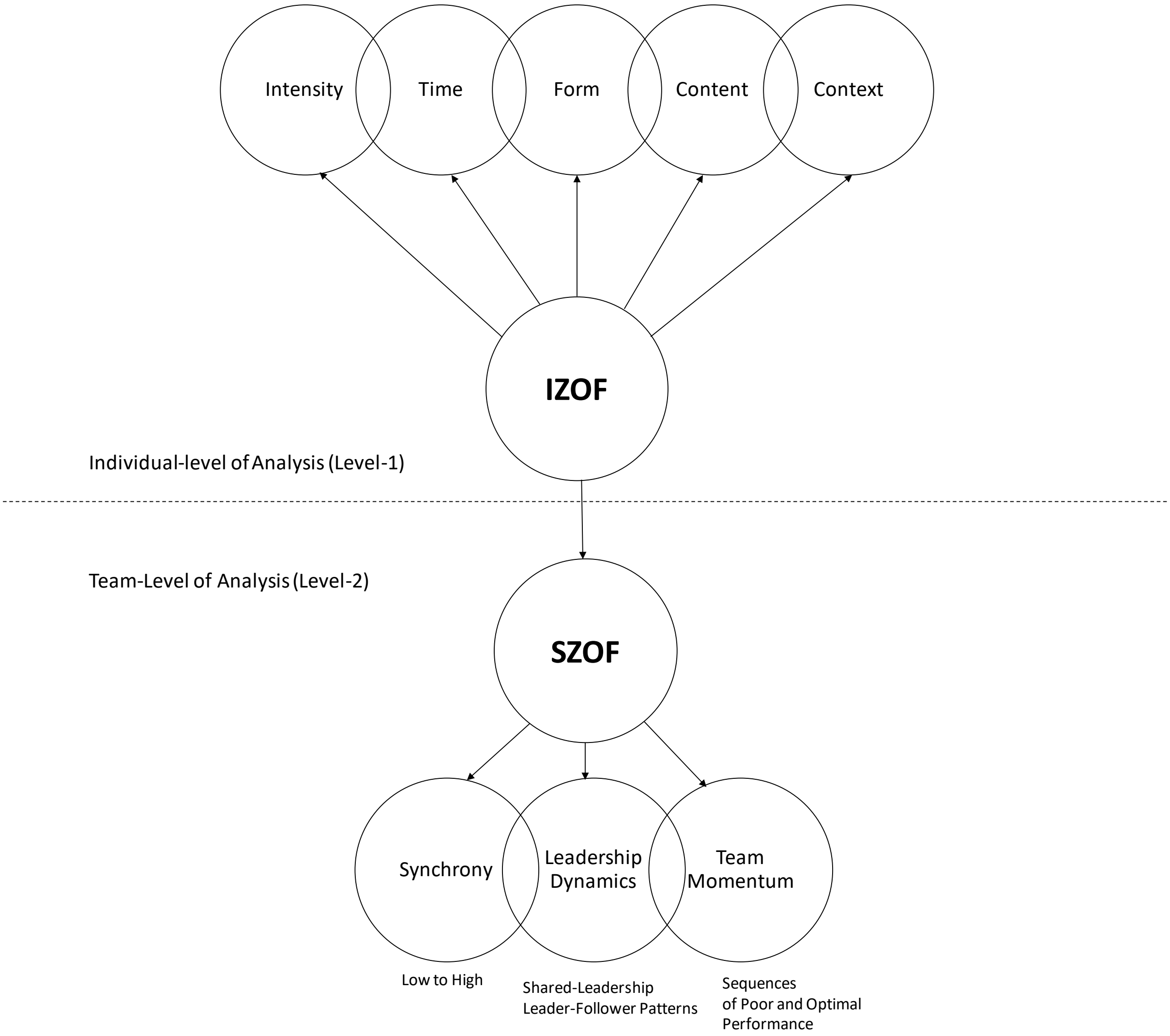

Figure 7. The IZOF is a formative indicator of the SZOF, which is a team-level construct. The SZOF framework possesses three measurable reflective indicators, namely within-teams' levels of synchrony, leadership dynamics, and team momentum patterns.