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Predicting the dynamic criteria of basketball players: The influence of the 'Big Five', job experience, and motivation

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ABSTRACT

The present study analyses the prediction of the effectiveness and its fluctuations of 34 semi-professional basketball players throughout a sport season using the dynamic criteria as theoretical framework. The predictor variables (the Big Five personality factors, job experience and motivation) were obtained by means of self-report, while effectiveness was determined through objective data (statistics of matches). The predictive models were developed using generalized maximum entropy formulation, and results show that: (1) the relevance of the predictors of effectiveness is different each time they are analysed; (2) all variables except conscientiousness predict the fluctuations, and openness to experience is the most influential predictor; and (3) job experience is less relevant than personality and motivation. Finally, some recommendations are made regarding the choice of predictors for the selection of basketball players.

La predicción de la dinámica de los criterios de los jugadores de baloncesto: influencia de los "cinco grandes", la experiencia laboral y la motivación

Palabras clave:
Dinámica de los criterios
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RESUMEN

En el presente artículo se analiza la predicción del rendimiento y de sus fluctuaciones en el ámbito del baloncesto. Con la dinámica de los criterios como marco teórico, se analizaron los resultados de 34 jugadores semi-profesionales durante una temporada deportiva. Los modelos predictivos se realizaron con la formulación de máxima entropía generalizada, utilizando como predictores la personalidad según el modelo de los *Big Five*, la experiencia, y la motivación intrínseca y como criterio se tomó la eficacia, con medidas objetivas. Los resultados obtenidos fueron los siguientes: (1) la importancia de los predictores varía a lo largo de la temporada, (2) el principal predictor de las fluctuaciones es el factor de personalidad "apertura a la experiencia", si bien todas las variables salvo el factor "responsabilidad" participan en el modelo predictivo y (3) la experiencia muestra una menor capacidad predictiva que los otros predictores. Finalmente, se hacen recomendaciones acerca de la elección de predictores en los procesos de selección de jugadores de baloncesto.

The personnel selection process encompasses the identification, measurement and prediction of knowledge, skills, abilities and other characteristics (KSAOs) that predict the job criteria established by the organization (Chan, 1998). The criteria used to be samples of workers' effectiveness and performance relevant to decision making processes in organizations (Austin & Villanova, 1992). However, despite their undeniable relevance, conceptualising the criteria is still difficult (e.g., García-Izquierdo & García-Izquierdo, 2006; Ones & Viswesvaran, 2002; Sackett & Lievens, 2008). These difficulties, also known as "criterion problem", are due to the dynamic, multidimensional, situation-specific, and multifunctional nature of criteria (Austin & Villanova, 1992). The present paper is focused on the first of these characteristics: the "dynamic criteria".

Interest in dynamic criteria has been growing since the 1960s, when the first studies were undertaken (Sackett & Lievens, 2008). Deadrick and Madigan (1990) have defined dynamic criteria as "systematic changes in critical job behaviours or outcomes over

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time" (p. 719) due to individual differences. Hence, the relationship between KSAOs and the criteria could be unstable (Sturman, 2007) and thereby decision-making in personnel selection should also consider fluctuations of criteria over time (Sonnentag & Frese, 2012). This study aims to contribute to a better understanding of dynamic criteria and their implications for personnel selection. In order to achieve this, we show how predictors such as the 'Big Five' personality factors, job experience, and intrinsic motivation change their relationship with criteria over the time, and that these variables predict fluctuations in criteria.

Theoretical framework: Dynamic criteria

Murphy (1989) developed the most widely accepted model of dynamic criteria. According to this model, in every job a person moves back and forth between two distinct stages: transition and maintenance. Transition takes place when an employee takes on a new job or changes the duties in his or her job. In this stage, workers learn how to deal with their tasks. Accordingly, cognitive, physical and psychomotor abilities become the main predictors of criteria. In the maintenance stage, workers know how to perform their tasks, and are not confronted with novel situations. Thus, in this stage criteria depend mainly on employees' dispositional variables (personality and motivation, but also interests and values). The duration of each stage depends both on the context and on individual differences.

As regards empirical research, Table 1 summarizes these studies and illustrates some significant points. First, researchers use abilities and dispositional variables as predictors, but also temporal variables, biodata, and other variables (e.g., job complexity or turnover). Second, all the studies use objective outcomes as criteria, such as sales and statistics. Third, the Big Five personality factors and job experience are the most frequently used predictors. Lastly, although motivation was considered by Murphy (1989) in his model and its influence on criteria is well accepted (Steers, Mowday, & Shapiro, 2004), none of these studies takes motivation into account.

Despite the fact that contributions show that criteria change during the maintenance stage (e.g., Hofmann, Jacobs, & Gerras, 1992; Ployhart & Hakel, 1998; Zickar & Slaughter, 1999) further research is needed on fluctuations in dynamic criteria (Sturman, 2007). As an example, using the analyses provided by the non-linear dynamical systems (NDS) theory, we have shown that criteria fluctuations are higher than was previously thought and that a non-linear order does exist behind patterns that appear to be random (García-Izquierdo, Ramos-Villagrasa, & Navarro, 2012; Ramos-Villagrasa, Navarro, & García-Izquierdo, 2012).

In view of the foregoing, this study contributes to the dynamic criteria literature in a number of important ways, namely by (1) developing predictive models of both dynamic criteria and their fluctuations; (2) including motivation in the predictive models; and (3) analysing the importance of dispositional variables in relation to job experience.

The present study

Our aim is to analyse predictive models of criteria and criteria fluctuations. The study reported here is based both on Murphy's (1989) model, and on the empirical research about dynamic criteria (e.g., Deadrick & Madigan, 1990; Ployhart & Hakel, 1998; Zyphur, Bradley, Landis, & Thoresen, 2008). At the same time, we keep doing our recent research in a basketball setting where we have found that dynamic criteria fluctuate substantially in the maintenance stage (García-Izquierdo et al., 2012). Specifically, with this study we move forward in searching how personality, motivation, and experience predict effectiveness and fluctuations in effectiveness of basketball players across the maintenance stage.

Table 1
Predictors of criteria throughout time

Study	Sample	Criterion	Set of predictors	Predictors
Day, Sin, and Chen (2004)	Hockey players	Match statistics	Temporal	Age Job experience Organizational tenure
			Biodata	Age at first captain Captain frequency Height Position Seasons played before captain
Deadrick and Madigan (1990)	Sewing machine operators	Average hourly piece/rate production earnings per week	Abilities	Cognitive ability Psychomotor ability
			Temporal	Job experience
Deadrick, Bennet, and Russell (1997)	Sewing machine operators	Average hourly piece/rate production earnings per week	Abilities Temporal	Psychomotor ability Job experience
Ployhart and Hakel (1998)	Securities analysts	Sales	Dispositional	Empathy Persuasion
			Biodata	Past salary and expectations
Stewart (1999)	Salesperson	New sales	Dispositional	Big five personality traits (conscientiousness)
Stewart and Nandkeolyar (2007)	Football players	Match statistics	Others	Job complexity
Sturman (2003)	Studies with different samples	Objective and subjective outcomes from prior studies	Temporal	Age Job experience Organizational tenure
Sturman and Trevor (2001)	Employees from a financial services organization	Fees generated from the loans sold	Biodata Other	Gender Turnover
Thoresen et al. (2004)	Salesperson	Sales	Dispositional	Big five personality traits
Zyphur et al. (2008)	Students	Student grade point average	Dispositional	Big five personality traits

We have included personality and experience among predictors, because of their proven relationship to criteria during the maintenance stage (e.g., Day, Sin, & Chen, 2004; Thoresen, Bradley, Bliese, & Thoresen., 2004; Zyphur et al., 2008). Personality was conceptualised using the Big Five factors model, the most widely accepted way to describe personality in the workplace (Salgado & de Fruyt, 2005). Several meta-analyses have shown that, along with objective criteria, conscientiousness is the factor with the highest predictive validity (Barrick, Mount, & Judge, 2001; Salgado & Táuriz, in press). As regards experience, there is substantial evidence supporting its contribution to the prediction of criteria, as the meta-analysis of Quiñones, Ford, and Teachout (1995) has shown. The last predictor in our study is motivation, in line with the emphasis that Murphy (1989) laid on this variable in the maintenance stage. Specifically, we analyse intrinsic motivation, because its contribution to the prediction of criteria is well accepted (Deci & Ryan, 2000; Gillet, Vallerand, & Rosnet, 2009; Steers et al., 2004).

On the basis of the aforementioned literature, we proceed with the hypotheses development. Firstly, the relationship between predictors and criterion may change over time as a consequence of dynamic criteria (Sturman, 2007). In that sense, we believe that changes could be different for each predictor. Regarding the Big Five factors, Lievens, Dilchert, and Ones (2009) have shown that personality-criteria relationship fluctuates over a seven-year period, with conscientiousness always having the highest predictive validity. These results are similar to those found in cross-sectional meta-analyses (e.g., Barrick et al., 2001) and, consequently, our first hypothesis goes as follows:

H1a: The relationship between Big Five personality and effectiveness will fluctuate over time.

H1b: Conscientiousness will always be more strongly related to effectiveness than the remaining personality factors.

Regarding experience, Sturman's (2003) meta-analysis has shown that the relationship between experience and criteria decreases over time, which is our second hypothesis:

H2: The relationship between experience and effectiveness tend to decrease over time.

As for our last predictor, intrinsic motivation, there is evidence suggesting huge fluctuations over time (e.g., Navarro & Arrieta, 2010). The research about motivation and dynamic criteria is scarce until now, but taking into account the instability of this variable, we hypothesize substantial changes in their predictive validity. Thus, our third hypothesis is as follows:

H3: Intrinsic motivation tends to change their relationship with effectiveness over time.

In addition to this, we will address the strength of predictors-criteria relationships. Since on one hand job experience facilitates task proficiency (e.g., Schmidt, Hunter, & Outerbridge, 1986), and on the other hand employees in the maintenance stage only perform well-learned and routine procedures (Murphy, 1989), we expect that experience will have less influence than dispositional variables. Then, we propose our fourth hypothesis:

H4: During maintenance stage, the Big Five personality factors and intrinsic motivation will be more relevant as predictors of effectiveness than experience.

Finally, our previous research mentioned above has shown that higher fluctuations are related to better results. In this regard, Sturman (2007) asserts that fluctuations and their implications for the predictors-criterion relationship should be recognized as different but related phenomena. Therefore, it seems reasonable to think that predictors of the criterion may also predict its fluctuations. To the best of our knowledge, there is no previous research that helps us to determine which variables are more relevant. Hence, our last hypothesis is as follows:

H5: Big Five personality factors, experience, and intrinsic motivation will be predictors of fluctuations in effectiveness.

Method

Participants

Participants in this study belong to four semi-professional basketball teams. Players of three teams (75%) are remunerated for their work. We removed the participants who did not play enough matches to evaluate their effectiveness (e.g., because they were injured or moved to another team) and also those who did not answer all the items in the questionnaires. Thus, our final number of participants was 34, with a balanced gender distribution (52.95% were men and 47.05% were women), age around 24 years (M = 24, SD = 3.77, and Mode = 22), and experience playing basketball between 60 and 336 months, (M = 159.32, SD =58.02, and Mode = 180).

Measures

Criteria and predictor variables were measured using different sources, avoiding the common method variance (Spector, 2006). Specifically, we use objective data for the criteria and self-report for the predictors.

Criteria:

Effectiveness. We used a set of objective variables grouped in a composite criterion developed by the Spanish National Basketball Association, called Statistics. This criterion contains information about the performance of players in every match of the season. To be able to make valid comparisons, each player's Statistics were adjusted for the amount of time played in each match. The final algorithm was:

$$S = \frac{(a + b + c + d + e + f) - (w + x + y + z)}{t} \quad (1)$$

, where S is the composite criterion Statistics, a is the number of points per game, b is the number of rebounds obtained per game, c is the number of assists per game, d is the number of steals per game, e is the number of personal fouls received per game, f is the number of blocked shots per game, w is the number of missed shots per game, x is the number of turnovers per game, y is the number of rebounds failed per game, z is the number of personal fouls committed per game, and t is the minutes played per game.

Our effectiveness variable was estimated by the mean Statistics of three matches in three different times: at the beginning, at the middle and at the end of the season.

Fluctuations. Fluctuations in effectiveness through time were calculated by the mean squared successive difference or MSSD (von Neumann, Kent, Bellinson, & Hart, 1941). The MSSD measures the instability of time series data, where higher values indicate high fluctuations of the time series. In our study, we calculated the MSSD of the Statistics measure.

Predictors:

Big Five personality factors. Personality factors were measured with the Spanish version of the scale developed by Benet-Martínez and John (1998). This instrument has 44 items with Likert-type responses ranging from 1 to 5. The five factors are listed below, along with the observed reliability, the number of items comprising each dimension, and a sample item: (1) emotional stability (α = .86): 8 items, "Is relaxed, handles stress well"; (2) extraversion (α = .77): 8 items, "Is talkative"; (3) openness to experience (α = .78): 10 items, "Is original, comes up with new ideas"; (4) agreeableness (α = .63): 9 items, "Likes to cooperate with others"; (5) conscientiousness (α = .63): 9 items, "Makes plans and follows through with them".

Job experience. Experience was measured with an item asking how long the participant has been competing in federated basketball. Answers were measured in months in order to facilitate comparisons between players.

Intrinsic motivation. It was measured with the corresponding subscale from the Spanish version of the Sport Motivation Scale

(Guzmán, Carratalá, García-Ferriol, & Carratalá, 2006). It has 8 Likert-type items, ranging from 1 to 5. A sample item is "I play basketball for the pleasure I feel while improving some of my weak points". Observed reliability was α = .91.

Procedure

This study used a longitudinal design involving the administration of questionnaires to the participants at the beginning (time 1), at the middle (time 2) and at the end (time 3) of the basketball season. Intrinsic motivation was measured each time while personality and experience were measured only at time 1. This is because personality is considered quite stable over time (Specht, Egloff, & Schmunkle, 2011) and the experience of all players has been increased in the same proportion over the course of the study.

As regards the criteria, the effectiveness data were collected in the three matches after the application of questionnaires in each time.

Analysis

We began by calculating the study's descriptive statistics and correlations. We analyzed the relationship between variables with the Spearman's correlations corrected by attenuation, and predictive models were developed with generalized maximum entropy (GME) formulation. GME is an analysis technique based on Information Theory. Its main advantage is that it enables solutions to be found even with limited or incomplete data (Moreno & López, 2007), such as in the case of a small sample size. As this technique has not been widely used in dynamic criteria research, we provide a brief description of its rationale. A detailed review of their calculation can be found in García-Izquierdo, Moreno, and García-Izquierdo (2010) and Golan, Judge, and Miller (1996).

Our starting point is quite similar to the traditional multiple regression. We want to explain criteria (Y) in basketball players according to our predictors (X_1, X_2... X_n), the contribution of each predictor (β_n), and an error term (u) by estimating $Y = \beta_n X_n + u$ under the GME. As there is no evidence that errors are not random, we use a uniform probability distribution to describe it, i.e. all values have the same probability. As regards predictors, we can take advantage of the available information (i.e., the values of the participants in predictors and criteria) to build a more accurate probability distribution than the uniform. This distribution is developed using an entropy measure and the probability axioms as restrictions in the estimation of the predictive model. The entropy measure was maximized to control that we are choosing the distribution for which our available information is just sufficient to determine the probability assignment. Different entropy measures exist, but we applied the Shannon's (1948) entropy, as is the most widely used.

However, the obtained model with this procedure is limited because the weights of all predictors are considered part of the same probability distribution. As a solution, we can move to a reparametrized model by turning the weight of each predictor to a variable with its own probability distribution, and do the same for the error in each participant. This leads to a more accurate model with an Information Index (R) which measures the uncertainty reduction in a 0-1 scale where 0 implies no informational value of the data set and 1 perfect in-sample prediction. In addition, the reparametrized model gives us an estimated weight ($\hat{\beta}_i$) for each predictor such as the β in traditional regression. Lastly, but equally important, the model gives us a measure for identifying which predictors explain the model. This measure is called normalized entropy measure or $S_i(p)$, which ranges between 0 and 1, and where lower values indicate that a predictor makes a real contribution to the model. Thus, only predictors with low $S_i(p)$ should be considered.

The reparametrization process implies some subjectivity because of the necessity of choosing vectors (called z for predictors and v for errors). It is recommended that v follow the three-sigma rule (Pukelsheim, 1994), i.e. the vector lays around three standard deviations from the criterion. Unfortunately, there is no three-sigma rule for z, only the recommendation that vectors be built in accordance with previous literature and that we can use an individual vector for each predictor for a more accurate model (Golan et al., 1996). The scarcity of studies with similar samples makes this kind of accuracy difficult. However, we know by prior literature that all the predictor variables we have chosen have a positive relationship with the criteria as we can see in Table 1. Taking this into account, we performed several analyses until we had symmetrical support vectors with the lowest v that makes the solution feasible, which in our data set was 0, 10, and 20. We choose three vectors because we do not know so much about the relationship under study, but in situations with more knowledge the number of vectors could grow to improve predictions.All analyses were performed with SPSS software except the GME analyses, which were performed with the free version of General Algebraic Modelling System (GAMS). The GAMS program, developed by Brooke, Kendrick, and Meeraus (1992), is specifically designed for modelling linear, non-linear and mixed integer optimisation problems and can be downloaded from the official web page (www.gams.com).

Results

Table 2 shows descriptive statistics and correlations between the variables of the study. Based on the standard deviation of the variables, we can state that high variability among participants exists.

The information provided by correlations indicates that only openness to experience is related to effectiveness, specifically at time 3 (r_s = .36, $p \leq .05$), and fluctuations have a positive relationship with effectiveness at time 1, 2 and 3. However, these results should be considered carefully due the sample size and their implications (e.g., high sampling error).

The next step was the use of GME to test the hypotheses. To obtain the weights (β) all the variables were standardized. Table 3 shows the results for all predictive models (i.e., time 1, time 2, time 3, and fluctuations). As we can see, all the predictive models have a high information index (between .95 and .97), which suggests a high uncertainty reduction.

Focusing on predictors, we should consider only those that substantially reduce uncertainty but the acceptable values should be chosen in accordance with our knowledge about the phenomena under study and the variables involved (Golan et al., 1996). In absence of previous studies in the basketball setting, we took into account predictors which clearly contribute to find a realistic distribution. Thus, only $S_i(p)$ values of .10 or less will be considered. Thus, at time 1 conscientiousness ($\hat{\beta}_i$ = .20, $S_i(p)$ = .09) and emotional stability ($\hat{\beta}_i$ = .07, $S_i(p)$ = .03) are the most influential predictors. At time 2 the main predictors are motivation ($\hat{\beta}_i$ = .13, $S_i(p)$ = .06) and conscientiousness ($\hat{\beta}_i$ = .08, $S_i(p)$ = .04). Finally, at time 3 motivation ($\hat{\beta}_i$ = .22, $S_i(p)$ = .10) and conscientiousness ($\hat{\beta}_i$ = .12, $S_i(p)$ = .01) are again the main predictors. It is remarkable that motivation increases their influence over time. It is also interesting to note that experience has the same size in all predictive models ($\hat{\beta}_i$ = .03, $S_i(p)$ = .01).

Our first hypothesis proposed that the relevance of the Big Five would be different each time, and in view of our results we deem H1 to be partially supported: There are changes between personality factors and effectiveness through time, excepting agreeableness (H1a). Additionally, as we predicted, conscientiousness is always the most important personality factor (H1b). As for H2, we expected a decrease in the influence of experience, but it remains at the same level. Thus, this hypothesis is not supported. About H3, it is supported because motivation shows changes in their predictive validity over time.

Table 2
Descriptive statistics and correlations

Variables	*M*	*SD*	Range	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Emotional stability	22.35	5.78	11 – 35	1												
2. Extraversion	25.53	5.24	12 – 34	-.01	1											
3. Openness to exp.	35.65	5.91	26 – 50	.17	.08	1										
4. Agreeableness	31.85	3.64	23 – 40	.38*	.30	.46**	1									
5. Conscientiousness	30.88	5.50	19 – 40	.15	.05	.18	.24	1								
6. Experience	159.32	58.02	60 – 336	.14	.04	.39	.40	.42*	1							
7. Motivation time 1	33.85	8.06	19 – 48	.10	.16	.08	.38*	.10	-.09	1						
8. Motivation time 2	37.06	6.83	22 – 48	-.13	.04	.03	.18	-.17	-.05	.62***	1					
9. Motivation time 3	36.41	9.68	16 – 48	.11	.12	-.01	.24	-.04	-.08	.66***	.76***	1				
10. Effectiv. time 1	7.55	6.15	-2.00 – 26.67	-.17	-.27	-.05	-.08	.05	-.10	.32	.15	.13	1			
11. Effectiv. time 2	6.75	6.49	-2.67 – 20.67	-.15	-.05	-.04	-.08	.18	.04	.11	-.01	-.03	.52**	1		
12. Effectiv. time 3	5.98	5.49	-1.00 – 21.67	-.07	.11	.36*	.08	.10	.03	.28	.24	.17	.37*	.34*	1	
13. Fluctuations	.70	.60	-.250 – 2.29	-.23	.01	.19	-.01	.28	.11	.04	.04	-.04	.56***	.63***	.64***	1

Note. N = 34. Correlations are corrected for attenuation. * = $p \le .05$, ** = $p \le .01$, *** = $p \le .001$.

Table 3
Predictive models using GME

	Effectiveness Time 1			Effectiveness Time 2			Effectiveness Time 3			Fluctuations		
	$\hat{\beta}_i$	$S_i(p)$	R	$\hat{\beta}_i$	$S_i(p)$	R	$\hat{\beta}_i$	$S_i(p)$	R	$\hat{\beta}_i$	$S_i(p)$	R
Emotional stability	.07	.03	.96	.05	.02	.97	.03	.01	.95	.03	.01	.96
Extraversion	.03	.01		.04	.02		.03	.02		.03	.01	
Openness to experience	.03	.01		.03	.01		.31	.13		.16	.07	
Agreeableness	.03	.01		.03	.01		.03	.01		.03	.01	
Conscientiousness	.20	.09		.08	.04		.12	.06		.26	.11	
Experience	.03	.01		.03	.01		.03	.01		.03	.01	
Motivation*	.28	.12		.13	.06		.22	.10		.06	.03	

Note. N = 34, $\hat{\beta}_i$ = Estimated weigh,. $S_i(p)$ = Normalized entropy, R = Information index. The support vectors for predictors (z) are the same for all of them (0 / 10 / 20). The error support vector (v) is the same for all models (-3 / 0 / 3).
*Motivation introduced in each model is the one corresponding to the time analyzed, that is, motivation time 1 was used to predict effectiveness time 1, motivation time 2 to effectiveness time 2, and motivation time 3 to effectiveness time 3. The predictive model of fluctuations was performed using motivation on time 1.

Taking these results together, we are going to deal with H4. The comparison between experience and dispositional variables show ambivalent results. On one hand, conscientiousness and motivation are more relevant as predictors than experience. On the other hand, we expected the same result for the remaining personality factors and this does not happen. Thus, we can consider H4 to be partially supported.

The last hypothesis is about the prediction of fluctuations. As we can see in Table 3 all predictors except conscientiousness are included in the model. Openness to experience is the main predictor ($\hat{\beta}_i$ = .16, $S_i(p)$ = .07), followed by motivation ($\hat{\beta}_i$ = .06, $S_i(p)$ = .03) and emotional stability, extraversion, agreeableness and experience (all of them with $\hat{\beta}_i$ = .03, $S_i(p)$ = 01). Thus, we consider H5 to be supported.

Discussion

In this study, we develop models capable of predicting the effectiveness of basketball players and fluctuations in their effectiveness throughout the season. Although our results should be considered carefully because of the particularities of the job and the scarce sample size, we can outline some findings: (1) the relevance of the predictors of effectiveness is different each time they are analysed; (2) all variables except conscientiousness predict the fluctuations, and openness to experience is the most influential predictor; and (3) job experience is less relevant than personality and motivation. Let us consider each of these findings.

Our study supports the idea that dynamic criteria influence the relationship between predictors and effectiveness. According to our findings, conscientiousness and openness to experience decrease their relationship with effectiveness as the season progresses. Emotional stability shows a similar evolution, while extraversion, agreeableness and experience remain low in all predictive models. In contrast, motivation progressively increases its predictive validity until becoming the main predictor at time 3.

Results regarding fluctuations have shown that the same variables used to predict criterion can be used to predict its fluctuations, especially openness to experience. Literature have shown that openness is related to training proficiency (Barrick et al., 2001), and promotes successful adaptation to changing situations (Pulakos, Arad, Donovan, & Plamondon, 2000) by adjusting efforts and results in harmony with the scenario. Our results provide support for the proposition that predictor-criteria relationships and fluctuations in criteria are different but related phenomena (Sturman, 2007). Both phenomena are interesting because the first helps to identify which predictors have a sustained relationship with criteria, while the latter contributes to find adaptive workers, something essential in organizations (Ilgen & Pulakos, 1999).

Regarding experience, the present study suggests that is a less important predictor than personality and motivation in the maintenance stage. Nonetheless, experience contributes to the prediction of fluctuations, probably because experienced people are able to deal more easily with unexpected situations arising at work, as more experienced players have more and better knowledge of their role and how to develop better strategies to implement it (García-Izquierdo & García-Izquierdo, 2002; García-Izquierdo, García-Izquierdo, & Ramos-Villagrasa, 2007).

According to these results, we recommend that personnel selection of basketball players relies in at least three dispositional variables: conscientiousness and intrinsic motivation, which are the main predictors along maintenance stage, and openness to experience, which is the main predictor of fluctuations.

Limitations and recommendations for further research

There is no doubt that this study has shortcomings that need to be addressed. First of all, we have analyzed the basketball setting, and we are not confident enough about the extrapolation our conclusions to other jobs. Besides that, the small number of participants is also a limitation for generalization of our study. Nevertheless, this situation gives us the opportunity to show the application of GME in this context. We thought that GME approach would be especially useful in applied settings, although sometimes practitioners only have data from a limited data set.

Continuing with limitations, our study does not include abilities within the predictors of criteria. Traditionally, abilities and personality variables are part of the personnel selection models as they both are important predictors of organizational behaviours (García-Izquierdo, et al., 2007). However, given that participants are on the same level of competition we expect that their abilities are similar (García-Izquierdo et al., 2012), giving more relevance to the role of dispositional variables. In any event, future research should verify this proposition.

Last but not least, our study was performed with semi-professional players. The literature has found some differences between professional and amateur players (e.g., Ibáñez, Feu, García, Parejo, & Cañadas, 2009). Thus, in order to replicate this study with professional players it would be necessary to ensure that our results can be applied to them.

Regarding future research, we would like to stress that more studies about fluctuations in criteria are needed, as well. We also believe that research with different dispositional variables as values and interests could help to achieve a better understanding of the maintenance stage. Additionally, we thought that future research should investigate also the transition stage to increase our knowledge about the changes in predictor-criteria relationships between and within stages. Furthermore, the empirical research often uses effectiveness to study dynamic criteria, but this criterion comprises multiple dimensions (Guion, 2011). Therefore, we strongly recommend the study of other dimensions like task performance and contextual performance. Along these lines, we recommend that further research develop studies with longer time series to predict the underlying patterns of fluctuations. This is an interesting matter because some patterns obtain better results than other (García-Izquierdo et al., 2012; Ramos-Villagrasa et al., 2012).

Finally, we believe that the dynamic criteria framework can be useful for typical and maximum performance research, which add valuable information to the personnel selection processes (Klehe & Anderson, 2007). There are certain similarities between the stages of the model developed by Murphy (1989) and the typical/maximum performance distinction. According to Klehe and Latham (2008), in typical performance episodes motivation is more important than abilities as in the maintenance stage. In contrast, maximum performance was predicted only by abilities as in the transition stage. It is clear that dynamic criteria stages and typical/maximum performance stages are different phenomena, but we encourage the merging of both literatures as a step forward in solving this part of the criterion problem.

Conflicts of interest

The authors of this article declare no conflicts of interest

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