Journal of Work and Organizational Psychology 31 (2015) 101–107

Journal of Work and Organizational Psychology

www.elsevier.es/rpto

# Individual differences in predicting occupational success: The effect of population heterogeneity

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ARTICLE INFO

*Article history:*
Received 21 October 2014
Accepted 24 March 2015

*Keywords:*
Latent class
Occupational attainment
Logistic regression mixture models

ABSTRACT

Using a sample of 339 university graduates from the University of Alicante (Spain) three years after completion of their studies, we studied the relationships between general intelligence (GI), personality traits, emotional intelligence (EI), academic performance, and occupational attainment and compared the results of conventional regression analysis with the results obtained from applying regression mixture models. The results reveal the influence of unobserved population heterogeneity (latent class) on the relationship between predictors and criteria and the improvement in the prediction obtained from applying regression mixture models compared to applying a conventional regression model.



## Diferencias individuales en la predicción del éxito ocupacional: el efecto de la heterogeneidad de la población

*Palabras clave:*
Clase latente
Consecución de empleo
Modelos mixtos de regresión logística

RESUMEN

Mediante una muestra de 339 graduados universitarios de la Universidad de Alicante, España, tres años después de acabar los estudios, hemos estudiado la relación entre inteligencia general (IG), rasgos de personalidad, inteligencia emocional (IE), rendimiento académico y consecución de empleo, comparando los resultados del análisis de regresión tradicional con los resultados obtenidos aplicando los modelos mixtos de regresión. Los resultados muestran la influencia de una heterogeneidad poblacional no observada (clase latente) en la relación entre predictores y criterios y la mejoría en la predicción a partir de la aplicación de los modelos mixtos de regresión en comparación con la aplicación del modelo convencional de regresión.



The transition from university to work is a complex phenomenon with many intervening factors, full of difficulties that are required for learning and the use of certain skills and competences (Rodriguez & Gutierrez, 2006; Vuolo, Mortimer, & Staff, 2013). Despite the importance of this period of time, the variables that facilitate success in this process of employability have not been included in many studies involving university graduates.

Most previous research has been based on global statistics (Organization for Economic Cooperation and Development - OECD, 1997; United Nations Educational, Scientific, and Cultural Organization - UNESCO, 1995) and has mainly focused on results or products (e.g., success-failure in graduates finding jobs, differences between degrees, efficacy, and performance) rather than on processes (e.g., adaptation between required education and received education, usefulness of what has been taught at university or job searching strategies). When the effect of process variables has been analysed at the beginning of professional careers (e.g., García-Montalvo, 2001; Moscati & Rostan, 2000; Paul & Murdoch, 2000; Woodley & Brennan, 2000), variables such as the field of study, gender, place of residence or complementary training have been

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http://dx.doi.org/10.1016/j.rpto.2015.03.002
1576-5962/

included; however, individual variables such as intelligence or personality have not been considered.

These types of variables have been included in studies focused on results. In these cases, the predictive validity of general intelligence, personality, and emotional intelligence has been shown (Abele & Spurk, 2009; Boudreau, Boswell & Judge, 2001; Ng, Eby, Sorensen, & Feldman, 2005; Nyhus & Pons, 2005; O'Boyle, Humphrey, Pollack, Hawver, & Story, 2011; Salgado, 1998; Van Rooy & Visweswaran, 2004; Wille, De Fruyt, & Feys, 2013), for more specific occupational attainment criteria (Castejon, Gilar, & Miñano, 2011; Cobb-Clark & Tan, 2011; García-Izquierdo & García-Izquierdo, 2002; Jackson, 2006; Schmidt & Hunter, 2004). For example, in relation to personality traits, the results suggest that e*xtraversion* and *conscientiousness* are valid predictors of occupational attainment (De Fruyt & Mervielde, 1999; Groves, 2005; Jackson, 2006).

However, in the field of relationships between predictors and criteria, it has not been easy until now to unequivocally establish the magnitude of these relationships when explaining different types of organizational outcomes. This situation is probably a result of factors such as the type of starting model, the type of measures used (both of predictors and criteria), the use of small or restricted samples, the fact that the relation between predictors and criteria may be only unidirectional, and the role of the location of the predictor within the predictor-criteria causal chain (Brackett & Mayer, 2003; MacCann, Matthews, Zeidner, & Roberts, 2003; Salgado et al., 2014; Salgado & Tauriz, 2014; Wille & De Fruyt, 2014). We therefore believe that the importance of these predictors is actually different from what has been previously determined (Kuncel, Ones, & Sackett 2010; Schmidt, Shaffer, & Oh, 2008), i.e., the magnitude of relationships between individual differences and criteria has been underestimated or overestimated. Therefore, if these aspects are considered, a different predictor-criteria association could be expected.

In addition to the previous characteristics, sources of *population heterogeneity* (whether observed or unobserved) can modulate the relationships between independent and dependent variables. If the sources of population heterogeneity are unobserved, the data can be analysed using latent class models (Lubke & Muthén, 2005), and observed sources of heterogeneity can be included as covariates. These models, which are also known as mixture modelling, use various methods and associated software that have been developed to analyse unobserved heterogeneity (Lubke & Muthén, 2005; Magidson & Vermunt, 2002), accounting for unobserved heterogeneity matters (Pozzoli, 2006).

The Latent Class (LC) regression model (Magidson & Vermunt, 2002) is used to predict a dependent variable as a function of predictors, including an R-category latent variable; each category represents a homogeneous population (class, segment), and different regressions are estimated for each population (for each latent class). The advantages over traditional regression models include relaxing the traditional assumption that the same model holds for all cases ($R = 1$) and allowing the development of separate regressions to be used to target each class.

The effects of these unobserved variables have been highlighted in a number of research studies in the educational field (Ding, 2006; Keefer, Parker, & Wood, 2012), although this has not been the case in the field relating to occupational attainment or employment success. Accordingly, it is important to carry out studies that explore the degree to which the influence of variables such as *general intelligence, personality traits*, and *emotional intelligence* can be more precisely specified when predicting professional attainment at a time that is crucial to guarantee later success: the early career stage.

It is for this reason that we have carried out this study, whose main objective is to establish whether the variables of *general intelligence* (as measured by an IQ test), the variables of *personality* (as measured by the Big Five), *emotional intelligence* (as measured by the TMMS-24), and *academic performance* (as measured by the mean academic achievement obtained during the university degree) differ across an unobserved potential class of individuals. The aim is to identify the relationships between occupational attainment and the predictor variables along with the number of latent classes that best fit the data and to test potential predictors for a given latent class, when observed variables such as gender, field of study, or type of studies are incorporated in the analysis as covariates.

To achieve this, we suggest the following hypothesis:

*Hypothesis 1*. The prediction obtained when taking into account the specific patterns, derived from the application of regression mixture models, will have greater explanatory power than the prediction obtained from the application of the conventional model.

*Hypothesis 2*. The relationships between some of the predictors (personality trait *openness)* and the criteria (*occupational attainment*) will vary according to the unobserved characteristics of the subpopulations (probability of working), so that they will produce a different effect according to the class that they belong to. In the specific case of this factor, it is expected to affect more negatively those who work than those who do not.

## Method

### *Participants and procedure*

The sample consisted of 339 university graduates from the University of Alicante (Spain), who reported whether they were working or not in a survey conducted three years after completing their studies. These 339 students (68% were women and 32% men, with a mean age of 26.4 years) had participated in a study three years earlier that assessed their personal and socio-emotional competences during their final year at university, having been selected through stratified random sampling proportional to the number of students enrolled in each of the fields of 1) science and technology (25.7%), 2) social sciences (18.9%), 3) education (24.5%), 4) bio-health (15.9%), and 5) humanities (6.5%).

In the first phase, conducted when students were enrolled in the final year of their degree, the NEO-FFI questionnaire was administered together with factor "g" test and the Trait Meta-Mood Scale-24 to an initial sample of 906 individuals. In 2012, three years after the first study, the initial sample was reduced to 339 graduates, comprising those who continued to participate after graduation by completing a questionnaire designed to collect information on the employment status of the graduates who took part in the first study and their entry into the labour market. The questionnaire, which took no more than 30 minutes to fill in, was administered online to be completed within a maximum period of three months after receipt.

### *Measures*

*General intelligence*. To measure general intelligence, we used the factor "g" test, scale 3 by R. B. Cattell and Cattell (1994), adapted to Spanish by TEA. This scale consists of four subtests: series, classification, matrices and conditions, enabling us to obtain the IQ of the sample. The "g" factor loadings are high, i.e., approximately 0.90.

*Personality*. This variable was measured with the Big Five Inventory (NEO-FFI, Costa & McCrae, 1992), a self-report measure of five personality dimensions: extraversion, agreeableness, conscientiousness, neuroticism, and openness; the short version employed in this study consists of 60 elements. The participants indicate their level of agreement with each item on a 5-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*). The value of Cronbach's alpha for the

final sample was .854 for Neuroticism, .821 for Extraversion, .772 for Openness, .775 for Agreeability, and .821 for Conscientiousness. Moreover, the value of Cronbach's alpha for the initial sample was .849 for Neuroticism, .827 for Extraversion, .753 for Openness, .748 for Agreeability, and .821 for Conscientiousness.

*Emotional Intelligence*. To measure EI, we used the Trait Meta-Mood Scale-24 (TMMS-24; Fernández-Berrocal, Extremera, & Ramos, 2004); the short Spanish version (24 items) of the Trait Meta-Mood Scale-48 by Salovey et al. (1995) measures three factors: a) attention to feelings, defined as the extent to which people attend to and value their feelings; b) clarity of feelings, defined as understanding one's feelings; and c) mood repair, defined as attempts to maintain pleasant moods or repair unpleasant ones. The participants indicate their level of agreement with each statement on a 5-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*). Cronbach's alpha for the final sample was .876 for Attention, .849 for Clarity, and .858 for Repair. In addition, Cronbach's alpha for the final sample was .886 for Attention, .863 for Clarity, and .847 for Repair.

*Academic performance.* This variable was operationalized using the average grade in the academic transcript. The grades ranged from 1 to 10 and were recorded to 1 decimal place.

*Occupational attainment.* Occupational attainment represents the level of success achieved by the student in finding a job after completing his or her studies. This dependent variable was dichotomous, with the employed participants codified as 1 and those not working as 2.

### *Data analysis*

The independent variables were continuous (num-fixed) and included the predictors TMMS-Attention, TMMS-Clarity, TMMS-Repair, neuroticism, extraversion, openness, agreeability, conscientiousness, IQ score, and mean academic achievement, with gender and the professional field as covariates. We implemented all of the data analyses with Latent GOLD® 4.5 (Magidson & Vermunt, 2005). The conventional logistic regression analysis was implemented with SPSS V.20.

## Results

Because the final sample employed in the present study was one-third of the original, to compare the possible restriction of range, descriptive statistics were calculated for each of the predicted variables, both in the final sample and the original sample (Table 1). As can be observed in the data, the means and standard deviations are quite similar between them.

In Table 2, the correlation matrix among variables is included. As can be observed, mean academic achievement only has a positive correlation with Conscientiousness, whereas occupational attainment does not show significant correlations with the rest of the variables.

With respect to the possible underestimation of the real correlations due to the restriction of the range in the employed sample of this study, observation of the data in Table 1 does not seem to indicate that they are strongly affected by the low variability of the sample employed in this work. For example, the real observed correlation between intelligence general factor score ("g" factor) and career general grade is $r = -.0200$, whereas the real corrected correlation as determined by employing the formula of Guiselli, Campbell, and Zedeck (1981) (in Salgado, 1997) is $r = -.0202$.

Logistic regression mixture models ranging from a 1-class latent model to a 3-class mixture model were tested. Based on empirical and substantive consideration, a 2-class logistic regression model was selected as optimal. In this 2-class model, the regression coefficients and error variance were class dependent and were freely estimated without any equality constraints. In our work, we follow the procedure described by Nylund, Asparouhov, & Muthén (2007, p. 543) to estimate the BLRT (Bootstrap Likelihood Radio Test), that is, the log likelihood difference distribution to obtain a *p* value, which indicates whether the *k*-1 class model is rejected in favour of the *k* class model. In a similar way, other indicators were also considered.

In the 1-class logistic regression model, $L^2 = 299.27$, the bootstrap *p*-value = .30 and the standard error (*SE*) = .02. In the 2-class logistic regression model, $L^2 = 245.93$, the bootstrap *p*-value = .09, and the *SE* = .01. In the 3-class logistic regression model, $L^2 = 191.42$, the bootstrap *p*-value = .008, and the *SE* = .004. The model $L^2$ statistic indicates the amount of association among the variables that remains unexplained after estimating the model; the lower the value, the better the fit of the model to the data. Other criterion for determining the number of class is to examine the *p*-value. Among models for which the *p*-value is greater than .05 (provides an adequate fit), the 2-class model is more explicative/predictive. In the logistic regression, the overall $R^2$ indicates how well the dependent variable is predicted by the model overall, similar to standard $R^2$ measures. In the 1-class logistic regression model, $R^2 = .05$, whereas in the 2-class logistic regression model, the overall $R^2 = .983$, with class one $R^2 = .97$, and class two $R^2 = .86$. The 3-class logistic regression model does not increase the variance explained by the model; the overall $R^2 = .987$.

To assess model improvement by using a conditional bootstrap, the difference (Bootstrap -2LL Difference) in $L^2$ between the 1-class and 2-class models is a measure of the amount of fit improvement associated with the 2-class model over the 1-class model. The results indicated (-2LL Difference = 53.33) that the estimated *p*-value associated with the increase in classes was .03 (with standard error of .008); therefore, as $p < .05$, this means that the 2-class model does provide a significant improvement over the 1-class model. Furthermore, the prediction error in the 1-class model was .2006, which in percentage terms is 20.06% (63 of the 314 participants); meanwhile, the percentage error in the 2-class model was .000 (all participants were well-classified).

Examination of the class-specific probabilities in the 2-class model shows that overall class 1 members are most likely to be working (97%) and class 2 members are most likely not to be working (80%). Class 1 consisted of 77% of the total sample, of which 64% were female and 36% male; among this 77% of the total sample, 24% were from fields 3 and 5, 21% from field 2, 18% from field 6, and only 5% from field 1. Class 2 consisted of 23% of the total sample, of which 72% were female and 28% male; class 2 had 31% students from field 5, 26% from field 3, and only 6% from field 6 and 4% from field 4.

Table 3 provides the regression coefficients for each of the two latent classes and the regression coefficients from the conventional logistic regression analysis, along with the estimated class proportions and covariates. The beta-effect estimates under the column labelled Class 1 indicates that class 1 is influenced in a positive way by the variable extraversion and conscientiousness; that is, a higher score in extraversion and conscientiousness is linked to having a higher chance of being employed (Yes) in class 1.

The beta effect is estimated under the column labelled Class 2, showing that Class 2 is influenced in a positive way by the variables TMMS-Attention, by extraversion, and by conscientiousness, indicating that a higher score in these variables is linked to a greater chance of entering the labour market, whereas Class 2 is influenced in a negative way by openness, indicating that a lower score in openness is linked to those who are employed (Yes), and vice versa, a higher score in this variable is more common in those who are unemployed (No).

Extraversion had more or less the same influence on both classes. The Wald statistic indicates that the difference in these

**Table 1**
Descriptive statistics of the variables in the study.

| | Minimum | Maximum | Mean | *SD* | Variance |
|---|---|---|---|---|---|
| Mean academic achievement | 3.05 (.00) | 9.73 (9.73) | 7.18 (7.05) | 0.72 (0.76) | 0.51 (0.58) |
| TMMS-Attention | 11 (8) | 40 (40) | 25.75 (25.70) | 5.84 (5.99) | 34.18 (35.94) |
| TMMS-Clarity | 13 (12) | 40 (40) | 26.93 (27.28) | 5.45 (5.54) | 29.72 (30.71) |
| TMMS-Repair | 12 (12) | 40 (40) | 28.54 (27.98) | 5.95 (5.86) | 35.41 (34.41) |
| Neuroticism | 12 (12) | 58 (60) | 31.82 (31.85) | 8.05 (7.82) | 64.95 (61.29) |
| Extraversion | 17 (17) | 60 (60) | 45.76 (45.58) | 6.50 (6.69) | 42.34 (44.76) |
| Openness | 24 (20) | 57 (58) | 42.23 (41.81) | 6.89 (6.60) | 47.47 (43.63) |
| Agreeability | 16 (12) | 57 (57) | 42.41 (42.54) | 6.48 (6.16) | 41.98 (37.96) |
| Conscientiousness | 28 (24) | 60 (60) | 45.81 (44.79) | 6.30 (6.42) | 39.77 (41.25) |
| IQ score | 7 (7) | 40 (40) | 27.07 (26.65) | 4.62 (4.66) | 21.42 (21.79) |

*Note*. Values in parentheses refer to the initial sample ($n = 906$).

**Table 2**
Intercorrelations between variables.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean academic achievement | 1 | | | | | | | | | | |
| Occupational attainment | −.081 | 1 | | | | | | | | | |
| TMMS-Attention | .049 | −.040 | 1 | | | | | | | | |
| TMMS-Clarity | .005 | .069 | .203** | 1 | | | | | | | |
| TMMS-Repair | −.034 | .012 | .168** | .463** | 1 | | | | | | |
| Neuroticism | −.004 | .038 | .387** | −.313** | −.394** | 1 | | | | | |
| Extraversion | .057 | −.083 | .088 | .272** | .332** | −.267** | 1 | | | | |
| Openness | .041 | −.036 | .256** | .241** | .362** | .021 | .223** | 1 | | | |
| Agreeability | .076 | .060 | .151** | .210** | .259** | −.174** | .219** | .188** | 1 | | |
| Conscientiousness | .291** | −.040 | .039 | .304 | .281** | −.227** | .270** | .212** | .214** | 1 | |
| IQ score | −.020 | −.012 | −.029 | .014 | .060 | −.082 | .043 | .012 | −.073 | −.016 | 1 |

*Note*. 1 = mean academic achievement, 2 = occupational atainment, 3 = TMMS-attention, 4 = TMMS-clarity, 5 = TMMS-repair, 6 = neuroticism, 7 = extraversion, 8 = openness, 9 = agreeability, 10 = conscientiousness, 11 = IQ score.
*$p < .001$.

beta effects in the classes is not significant (W = 0.0032, $p = .96$). This means that the two classes showed extraversion to the same degree. A similar situation was noted with conscientiousness (W = 0.50, $p = .48$).

The gamma parameters of the model for the latent distribution appear under the heading "covariates". The $p$-value associated with the Wald statistic shows that the overall effect for gender was non-significant (W = 3.26, $p = .07$), whereas the effect for the field of study was significant (W = 15.05, $p = .01$). Figure 1 displays a profile plot for the 2-class model. By default, the last categories for gender and field of study variables are displayed.

To contrast the latent logistic regression analysis with the conventional logistic regression analysis, a logistic regression analysis was performed with the same dependent variable and independent variables, while controlling for gender and field of study. The results are shown in the right column of Table 1. It can be seen that occupational attainment was significantly related to TMMS-attention in a positive way and to TMMS-clarity in a negative way. It is important to note the low percentage of variance explained by the conventional logistic regression ($R^2 = .05$).

Furthermore, the 2-class model helps to interpret the results obtained with the entire sample, considering the different subpopulations that comprise it, given that a single equation for the entire sample does not make adequate predictions and incorrectly classifies the participants who are unemployed (20.06%), whereas the 2-class model classifies the participants correctly.

## Discussion

The results show the advantages of using linear regression mixture analysis instead of the conventional regression model when analyzing the relationships between independent variables and dependent variables. When comparing the conventional regression analysis–or logistic regression analysis–this assumes that one equation would fit all participants. A latent class logistic regression analysis can provide a description of subpopulations of participants within a sample. Thus, latent class regression analysis may improve predictability because the subgroup differences are systematically classified to form homogeneous groups, which supports the first hypothesis suggested in this study. In the present study, the results of latent class logistic regression analysis are evidenced with the

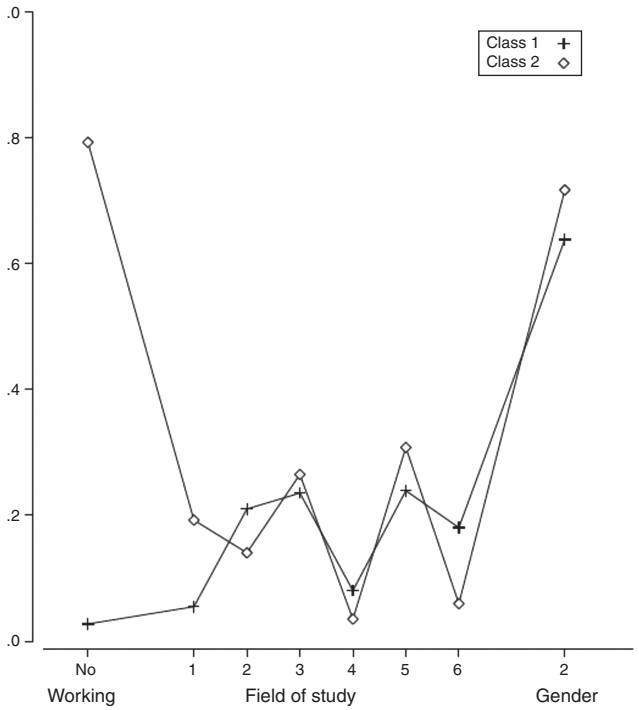


**Figure 1.** Profile plot for the 2-class model.

**Table 3**
Parameter estimates and model class size.

| | Class 1 | Class 2 | Conventional logistic regression analysis |
|---|---|---|---|
| Class proportion size | 77% | 23% | |
| Occupational attainment | 97% | 20% | |
| | Regression | Coefficients b[b] | b[a] |
| Total *g*-factor Test | .13 | .45 | −.007 |
| | (0.97) | (1.89) | (−0.46) |
| Neuroticism | −.21 | −.06 | −.02 |
| | (−1.05) | (−0.90) | (−1.81) |
| Extraversion | .44* | .45* | .02 |
| | (2.12) | (2.11) | (1.52) |
| Openness | .09 | −.43* | .001 |
| | (0.65) | (−2.03) | (0.09) |
| Agreeableness | −.40 | −.08 | −.02 |
| | (−1.48) | (−1.18) | (−1.88) |
| Conscientiousness | .52* | .29* | .009 |
| | (1.97) | (1.98) | (0.76) |
| TMMS-Attention | .11 | . 46* | .03* |
| | (0.57) | (2.02) | (2.03) |
| TMMS-Clarity | −.67 | −.23 | −.04* |
| | (−1.78) | (−1.80) | (−2.37) |
| TMMS-Repair | −.61 | .19 | −.01 |
| | (−1.87) | (1.42) | (−0.84) |
| Mean academic achievement | −1.47 | −.32 | .10 |
| $R^2$ | (−0.85) | (−0.56) | (0.96) |
| | .97 | . 86 | .05 |
| **Covariates** | | | |
| *Gender* | | | |
| Male | .18 | −.18 | |
| | (1.80) | (−1.80) | |
| Female | −.18 | .18 | |
| | (−1.80) | (1.80) | |
| *Field of study* | | | |
| 1 | −.65* | .65* | |
| | (−3.08) | (3.08) | |
| 2 | .13 | −.13 | |
| | (0.66) | (−0.66) | |
| 3 | −.08 | .08 | |
| | (−0.51) | (0.51) | |
| 4 | .39 | −.39 | |
| | (1.21) | (−1.21) | |
| 5 | −.34 | .34 | |
| | (−1.90) | (1.90) | |
| 6 | .56* | −.56* | |
| | (2.09) | (−2-09) | |

*Note*. Standard scores *z*, associated with parameters estimates, are in parentheses.
[a] Indicates regression coefficients from conventional logistic regression analysis.
[b] indicates logistic regression coefficients assuming yes (he/she is working as value of reference).
* $p < .05$.

existence of two subpopulations with specific patterns of regression function.

Second, the findings indicated that the personality traits of extraversion and consciousness were statistically significant in predicting occupational attainment throughout both latent classes, but other predictors such as openness or TMMA-attention were statistically significant only for distinct subgroups of graduates (class 2).

Regarding the first group of results, they show the positive correlation with the occupational attainment criteria, in line with the results obtained in other studies regarding these variables and other professional success criteria, such as salary (Gelissen & De Graaf, 2006; Judge, Higgins, Thoreson, & Barrick, 1999; Seibert & Kraimer, 2001; Sutin, Costa, Miech, & Eaton, 2009) or job satisfaction (Boudreau et al., 2001; Seibert & Kraimer, 2001). However, they also show the most generalizable character of the relationship of these variables based on a larger variety of different samples.

With regard to the second type of results, these bring to light the importance of the personality trait Openness (negatively), which confirms the second hypothesis and helps to resolve the discrepancies about the direction of the influence of this factor in previous studies, given that in some cases positive relationships with similar criteria had been found (Ng et al., 2005; Van der Linden, Te Nijenhuis, & Bakker, 2010), whereas in other cases there were negative relationships (Furnham, Taylor & Chamorro-Premuzic, 2008; Gelissen & De Graaf, 2006) or no relationship (Boudreau et al., 2001).

Respecting the positive relationship of the dimension of emotional intelligence TMMS-attention (not provided in the hypothesis), the results are aligned with previous studies for other success criteria (Bozionelos, 2004; Gelissen & De Graaf, 2006; Seibert & Kraimer, 2001), but these effects did not occur for the complete sample and only appear in group 2, which makes them different from the first group in the lesser likelihood of working.

An explanation of this different effect, according to the class that they belong to, is that participants with a lower probability of working are more sensitive to the negative effect of openness and positive TMMS-attention, unlike participants who achieve a job with a higher probability compared to those who would not be affected by having a higher distraction level or larger professional interests, or paying more attention to their own emotions, aspects that can distance people from their objectives. In summary, it is apparent that the dispersion or breadth of interests or objectives, and the capability to attend one's own emotions, distinctly

affect graduates according to the success they have had in finding employment. For those who do not find work, being more aware of their own emotions and not being open to multiple options when looking for a job at the beginning of the professional career could be the key for this group, whereas for those who are working, these variables are not relevant.

When evaluating the results, it is important to consider the study's strengths and limitations. The main limitation of this study concerns the sample size. The present study may have lacked sufficient power to corroborate the statistical significance of the relationships that have been found using larger samples. Another limitation, derived from the size of the sample, is the impossibility of disaggregating the samples for close examination of the possible different behaviors of the studied variables. Moreover, latent class regression analysis has its own limitations. For example, if there exists non-normality within the classes, non-normality of observed variables, or non-linearity, the latent class may simply describe the skewness and may not reflect the latent classes of the individuals in the sample (Bauer & Curran, 2003). We must recognize that classifying individuals into latent classes is model dependent and is not intrinsic to the individuals in the sample (Lubke & Muthén, 2005).

What makes this contribution of interest is that this is the first time that this new approximation has been used, which enables an improvement in the precision of prediction equations in the field of career success, based on individual variables, cognitive, personality, and emotional intelligence, using a longitudinal approach. Including the variability resources that are not observed in the object study samples will allow us to establish more precise relationships between these individual variables and occupational attainment. If the relationships between these predictors and success at the initial phases of a career are more precisely known, adequate policies and interventions could be designed to improve the quality of selection processes on behalf of organizations, and orientation, training, and development programs for graduates on behalf of educational institutions.

This study shows the importance of including new methods of analyzing data, such as logistic regression analysis, in studies on predictive validity both in the field of psychology at work and at organizations, and in the field of education, which will allow us to perfect the *recruitment* processes and use it as a base to *develop training actions* on social and emotional competences aimed at university students. These types of formative actions, which could be taught not only during the university courses, but also in bachelor or job training, could be used in attention-training workshops to focus on more important aspects of job search or one's own emotions. The development of this focused process feedback has been shown to be the key not only in this field but also in many other walks of life, as Goleman (2013) has noted.

## Conflict of interest

The authors of this article declare no conflict of interest.

## Financial support

This study was part of the research project ref. PSI2009-12696, funded by the Spanish Ministry of Science and Innovation.

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