Journal of Work and Organizational Psychology (2019) 35(2) 53-64

Journal of Work and Organizational Psychology

https://journals.copmadrid.org/jwop

LinkedIn "Big Four": Job Performance Validation in the ICT Sector

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ARTICLE INFO

Article history:
Received 8 February 2019
Accepted 29 March 2019
Available online 21 June 2019

Keywords:
LinkedIn
Personnel selection
Assessment
Criterion oriented validity
Incumbents
Social network websites

A B S T R A C T

Social networks websites, and specially the LinkedIn platform, have changed the landscape of recruitment and personnel selection to a unified organizational process. Thus, apart from using LinkedIn as a recruitment tool, professionals also use it to make evaluative inferences regarding the individual characteristics of the candidates (e.g., their personality). However, most of the research focused on LinkedIn has left aside the evidence about its validity for decision making in the work setting. In our study we analyze the criterion oriented validity of LinkedIn incumbents professional profiles (N = 615) in the information and communication technology (ICT) sector with some measures of job performance. The results show four major factors underlying LinkedIn profiles about professional experience, social capital, updating knowledge, and non-profesional information. These factors are significantly related to productivity, absenteeism, and the potential for professional development. These findings are discussed in light of their theoretical and practical implications.

Los "cuatro grandes" de LinkedIn: la validación del desempeño en el sector de las tecnologías de la información y la comunicación

Palabras clave:
LinkedIn
Selección de personal
Evaluación
Validez orientada a criterios
Empleados
Redes sociales

R E S U M E N

Las redes sociales, y especialmente la plataforma LinkedIn, están convirtiendo la función de reclutamiento y selección de personal en un proceso cada vez más unificado. Además de como herramienta de reclutamiento, los profesionales utilizan esta plataforma para hacer inferencias de evaluación sobre las características individuales de los candidatos, aunque la mayoría de las investigaciones han dejado de lado el análisis de su validez para la toma de decisiones en el entorno laboral. En nuestra investigación hemos estudiado los perfiles profesionales en LinkedIn de trabajadores del sector de las tecnologías de la información y la comunicación (N = 615), y su validez orientada a criterios de desempeño laboral. Los resultados muestran cuatro factores principales que subyacen a los perfiles de LinkedIn: experiencia profesional, capital social, actualización de conocimientos e información complementaria. Estos factores están significativamente relacionados con la productividad, el absentismo y el potencial de desarrollo profesional. Estos hallazgos se discuten a la luz de sus implicaciones teóricas y prácticas.

Information technology is dramatically changing society and work relations nowadays. Different ways of connecting through the Internet and the emergence of social networks have provided the means for individuals to contribute and share personal and professional information affecting the way of accessing the job market. In many cases this is in an unstructured mode, although professional websites often require that information is standardized. The quality of the data offered in professional web portals makes it possible to extract more information than in traditional methods (Zide, Elman, & Shahani-Denning, 2014), and additional aspects can be obtained, such as, for example, social capital (Reiners & Alexander, 2013). Moreover, as using these resources has a low cost (Nikolaou, 2014; Roth, Bobko, Van Iddekinge, & Thatcher, 2016), they are an element of great added value for personnel management in different organizational processes (Madia, 2011), such as recruitment, selection, or hiring. Therefore, companies that do not use social networks in their processes for contacting clients and potential employees are missing a huge opportunity. Specifically, the automated analysis of candidates' profiles to determine the adjustment to a position offers a significant efficiency gain in the process (Faliagka et al., 2014). However, it is true that today most organizations with implemented human resource policies use social networks to a greater or lesser extent. One of the most common uses is electronic recruitment, a form of external recruitment based

Cite this article as: Aguado, D., Andrés, J. C., García-Izquierdo, A. L., & Rodríguez, J. (2019). LinkedIn "big four": Job performance validation in the ICT sector. *Journal of Work and Organizational Psychology, 35*, 53-64. https://doi.org/10.5093/jwop2019a7 [Antonio García-Izquierdo and David Aguado were the guest editors for this article].

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on the Internet (Pfielffelmann, Wagner & Libkuman, 2010), which, according to Stone, Lukaszewski, Stone-Romero, and Johnson (2013), aims to provide a set of candidates who have the competences that fit the job vacancies of an organization. Today, recruitment and selection can be understood as a set, diluting the traditional border between recruitment and selection (Wilton, 2016), so that there is a decision-making process during the recruitment phase adding to this a strong evaluation shape (Aguado, Rico, Rubio, & Fernández, 2016). Following the attraction-selection-attrition model (e.g., Schneider, 1987; Wanous, 1992), it consists of a bilateral individual-organization fit, in which there is a mutual decision-making process based on an individual's interests, needs, capacities and personality, together with an organization's possibilities of satisfying them, and also to what extent these individual characteristics fit an organization's values, needs, and culture. The consequences of a good fit are greater satisfaction and greater commitment, while the consequences of a bad fit include, for example, low satisfaction and stress (Kristof-Brown & Guay, 2011). From this perspective, Web 2.0 allows the interaction between candidates and companies, providing a dynamic and bilateral communication environment, as connectivity and information-sharing are the main characteristics that make social media an interesting resource (Landers & Schmidt, 2016) for organizations. In this context, personnel selection is probably the human resources process that uses social networks most intensively. The data obtained in the Society for Human Resource Management survey (2015) showed that 56% of organizations used social network websites to find applicants, whilst in 2008 34% of the companies had used these sites for HR processes.

From the candidates' point of view, almost half of the job seekers in the world use social networks to some extent (Randstad, 2015). In Spain, these percentage increased in one year by 22% according to the Spanish National Institute of Statistics (INE, 2017). In the same line, Jobvite (2014) job portal reported that 93% of recruiting companies reviewed the candidates' profiles on social networks before making a hiring decision, and it has been found that 43% reconsidered their decision based on the profile (CareerBuilder, 2009). Thus, the last report of the Jobvite employment portal states that (a) more than half of the recruiters re-assess a candidate when they analyse their profile on social networks (61% of them being negative); (b) one third of them have directly rejected candidates based on the information contained in social networks; and (c) companys' human resource managers consider that candidates who are active users of social networks are more employable. In fact, approximately half of the organizations in the United States make a Google search in the process of selecting personnel (Roth et al., 2016), where LinkedIn is the social network most used in personnel selection. However, this frequency of use has not been accompanied by a systematic study of how useful information in social networks is, nor by a study of the possible biases of recruiters when they use them or, in short, of the different properties and quality of social networks as recruitment and selection tools, aspects that different authors have claimed they have (Aguado et al., 2016; Brown & Vaughn, 2011; Nikolaou, 2014; Seiter & Hatch, 2005; Van Iddekinge, Lanivich, Roth, & Junco, 2016). In fact, the few studies on electronic recruitment have not shown clearly whether or not social networks represent an improvement in attracting talent and diversity to organizations (McManus & Ferguson, 2003). In this context, the study of the above characteristics is relevant and takes on a special meaning in the case of Information and Communication Technology (ICT) professionals, since they are one of the main players in the job market. Just over 22% of world production is linked to the digital economy and this percentage will increase to 25% in 2020 (Accenture Strategy, 2016).

In this study we analyse LinkedIn profiles of ICT employees in order to answer the following questions: (1) is there an underlying structure to the information that candidates include in their LinkedIn profiles? (2) is there a relationship between the way candidates shape their professional profile on LinkedIn and their professional performance? (3) does the design of ICT professionals' profile vary based on their professional experience, gender, or geographical location?

Theoretical Foundations

The ICT Job Market

The ICT sector is present in all other production and service sectors, and its importance stands out in most studies on the job market as the growth of the world's leading economies seems to rely on advanced training in Science, Technology, Engineering, and Mathematics (STEM). According to the forecasts made by the EU for the technological sector, employment will grow by almost 900,000 jobs (Infoempleo, 2017).

In view of these data, it is not surprising that 69% of employers expect competition in search for professionals to increase (LinkedIn, 2018). Consequently, companies make substantial investments on developing recruitment based on SNW (from the former Storage Networking Websites) in order to attract talent, using references from colleagues and friends, and mobile devices (Jobvite, 2014) also. An analysis of the main employment portal used in Spain (InfoJobs) with data for 2015 shows that some of the highest number of vacancies are in the Computer and Telecommunications category (14.3% of the total number of vacancies), only behind the Commercial and Sales category (31.7% of the total number of vacancies) and ahead of the Customer Service category (13.8% of the total number of vacancies). The annual data show that the Computing and Telecommunications category grew 54.5% compared to the previous year (Infojobs, 2015).

LinkedIn as a Selection Tool

LinkedIn is the most widely used professional SNW (Kluemper, Mitra, & Wang, 2016; Ollington, Gibb, & Harcourt, 2013; van Dijck, 2013), specifically designed for professional networking looking for jobs and recruitment (Girard & Fallery, 2010; van Dijck, 2013). According to the report of Bullhorn Reach's (2014) employment platform, LinkedIn is the main social network for professionals used for recruitment and selection (97% of professionals reported using it, while only 19% and 21% report they use Facebook and Twitter respectively). Candidates, in fact, feel that LinkedIn is the only SNW that is effective for looking for a job (Adecco Global Report, 2014). In addition, they react more positively to its use in recruitment and selection processes than other non-professional SNW, such as Facebook or Twitter (Aguado et al., 2016). LinkedIn is so important in the recruitment and selection process that a recent article in *The Economist*, "LinkedIn: Workers of the world, log in" (The Economist, 2014, August 18), pointed out that the intensity of its use is strongly modifying the external recruitment agency market, reducing it from 70% to 16%. Beyond using LinkedIn to attract good candidates through good positioning (Madia, 2011), and the efficiency provided by the platform with new assessment tools (Kluemper, Rosen, & Mossholder, 2012), recruiters systematically use LinkedIn to make value judgments of the fit between candidates and organization as well as inferences about their future professional performance (Zide et al., 2014).

In recent years there has been some research on LinkedIn as a recruiting tool (e.g., Chiang & Suen, 2015; Davison, Maraist, & Bing, 2011; Girard & Fallery, 2010; Nikolaou, 2014; Ollington et al., 2013; Vicknair, Elkersh, Yancey, & Budden, 2010) in which the main approach has been to explore how recruiting and selection professionals make decisions based on the information contained in the profiles and to analyse the opportunities and barriers of its use, but more research is needed (Aguado et al., 2016; Kluemper et al., 2016) as academics and professionals demand good tools for good decisions. In particular, there is scarce information about its psychometrics properties, specially criterion oriented validity, that is, the relationship between LinkedIn profile and job performance, which will be studied in the empirical section of this paper.

Studies on other SNW (particularly Facebook) have provided evidence and, somehow, a road map about the research that needs to be carried out on LinkedIn. The studies on SNW as selection tools have been focused on analysing three key points: (a) inferences made by recruiters about person-organization (P-O) fit; (b) biases of recruiters in the decision making process; and (c) the problem of the accuracy of the information related with impression management. Let us now deal with this points. First, the scientific literature indicates how SNW can be used effectively in the decision making process for recruitment and selection. For example, recruiters analyse the information available on Facebook and it seems they are able to make good personality predictions (Chamorro-Premuzic & Steinmetz, 2013), even when applying complex automatic systems (Back et al., 2010; Kluemper et al., 2012). Recruiters use this information to obtain good indicators of P-O fit (Roulin & Bangerter, 2013). In the case of LinkedIn, Caers and Castelyns (2011) found that recruiters believed they were able to determine conscientiousness, emotional stability, and maturity. Therefore, they were able to make long-term predictions about whether a candidate was likely to leave or remain in the company as well as about the quality of their performance (Van Iddekinge et al., 2016). Nonetheless, reliability and validity and scoring are nowadays major concerns in social media usage (Landers & Schmidt, 2016).

Second, research clearly indicates how recruiters can sometimes be biased because they use information that is not related to job performance (Brown & Vaughn, 2011; Dubois & Pansu, 2004; Purkiss, Perrewé, Gillespie, Mayes, & Ferris, 2006; Seiter & Hatch, 2005; Shannon & Stark, 2003), and therefore their decision-making process could be discriminatory (García-Izquierdo, Ramos-Villagrasa, & Castaño, 2015). The most prominent of this irrelevant information is perhaps the biases produced when decisions are made based on age (Lahey, 2008; Maurer, & Rafuse, 2001; Weiss & Maurer, 2004), gender (Harvie, Marshall-McCaskey, & Johnston, 1998; Riach & Rich, 2002; Swim Aikin, Hall, & Hunter, 1995), sexual orientation (Black, Makar, Sanders, & Taylor, 2003; Blandford, 2003; Drydakis, 2009; Weichselbaumer, 2003), race (Kawakami, Dion, & Dovidio, 1998; Pager, 2003; Riach & Rich, 2002), or physical attractiveness (Luxen & Van de Vijver, 2006; Tews, Stafford, & Zhu, 2009). Undoubtedly, this poses a problem for the quality of selection decisions, and the use of SNW does not seem to alleviate this issue (Caers & Castelyns, 2011). On the contrary, online information is more abundant and recruiters have to process it equally for decision-making. For example, professional profiles that have a photo are significantly more viewed by recruiters (LinkedIn User Statistics and Demographics, LUSD, 2015 13/8/2015). This implies that some users have more opportunities than others due to the degree to which their profile is developed, regardless of job-related skills, and some may be dropped because of demographic features or the digital barrier (McManus & Ferguson, 2003). As a consequence, these tools are not completely free from adverse impacts (Van Iddekinge et al., 2016).

Third, and finally, it is a fact that organizations and recruiters form e-impressions of people based on the data contained in SNW (Spon, 2010). In line with this, SNW users develop their professional profile with the aim of being considered eligible for interesting vacancies. This often involves self-promotion and narcissistic self-presentation (Mehdizadeh, 2010; Nistor & Stanciu, 2017) with the objective of making their profile popular (Christofides, Muise, & Desmarais, 2009) within a more or less intentional strategy of creating an online personality (Boyd & Ellison, 2008; Marcus, Machilek, & Schütz, 2006). In spite of this, it has been pointed out that recruiters consider the information contained in the SNW profiles as more honest than the information presented in a résumé paper (Guillory & Hancock, 2012), perhaps because it is information that others can also see (for example, ex-workmates) and could make comments about its truthfulness.

In summary, it seems clear that recruiters regularly use SNW to search for candidates, and they also process that information to make inferences about the P-O fit (Bohnert & Ross, 2010). However, the models that explain parsimoniously the large amount of LinkedIn information and its connection to job performance have not been explored enough yet.

The first question is a basic one. The rigorous analysis of any instrument used for selection purposes needs to study the underlying structure of the different elements that are used in the tool. Is the information contained in LinkedIn profiles (e.g., presence or absence of photo, number of identified hobbies, etc.) simply a set of scattered aspects or it has a particular coherent structure? Personality studies have undeniably benefited from using a common frame of reference, such as the Five Factor Model (e.g., McCrae & Costa, 1999) and the model of competencies (e.g., Kurz & Bartram, 2002), since those models facilitate interpretation. Therefore, we expect that an in-depth study of LinkedIn as a selection tool will be benefitted from using general models that make it possible to summarize coherently and meaningfully the information available in the professional profiles. The information content that LinkedIn deploys is fundamentally related to biodata. Biodata are used in personnel selection through gathering and measuring information about past experiences, behaviours, and feelings in specific situations (Stokes, 1999). Biodata have demonstrated to be valid in different contexts (Allworth & Hesketh, 2000; Rothstein, Schmidt, Erwin, Owens, & Sparks, 1990; Salgado, Viswesvaran, & Ones, 2001), be resistant to faking (e.g., Schmitt & Kunce, 2002; Brown & Vaughan, 2011), generate positive applicant reactions (Anderson, Salgado, & Hülsheger, 2010), and be consistent between traditional (paper and pencil) and online versions (Ployhart, Weekley, Holtz, & Kemp, 2003). Nonetheless, biodata have some disadvantages, mainly related to construct and content validity (Stokes & Cooper, 2001). This means that although they are good performance predictors, research does not provide any evidence on how the process works (Becton Matthews, Hartley, & Whitaker, 2009) and are not free from adverse impact (Bobko & Roth, 2013). One main concern is about their relation with job performance. Thus, one of our main objectives is to determine the relationship between LinkedIn information and job performance by means of a criterion oriented validation study. Consequently, we aim to deal with some job performance issues. Job performance can be considered as the main contribution a worker makes to an organization (Arvey & Murphy, 1998), defined as the behaviours under an individual's control and relevant for organization's goals (Campbell, 1990; Rotundo & Sackett, 2002). The job performance dimensions most widely used are task and contextual dimensions (Moscoso, Salgado, & Anderson, 2017). The task dimension concerns core technical activities, and the contextual dimension concerns an employee's contributions that go beyond the technical obligations of work and help the organization to reach its goals (e.g., helping, cooperating, self-development, initiative, extra-effort, etc.). In addition, there is a counterproductive dimension that concerns behaviours that go against organizational goals (e.g., Spector & Fox, 2005). In this context, considering the potential use of LinkedIn to predict job performance, the reported studies have focused on analysing how recruiters make this prediction considering the data contained in the profiles, but do not focus so much on the data about profiles themselves. Analysing data about the profiles would provide us with relevant information about the validity of the information contained in profiles, regardless of the quality with which professionals use it. In fact, the analysis of this data would offer recruitment and selection professionals evidence of how to orient the analysis of profile information in order to predict a candidate's future job performance, and inform candidates how to manage their profiles. So, we have designed a criterion oriented validity study, and in line with this we propose the following research questions:

Research Question 1: Is there a coherent structure that underlies the information that candidates include in their LinkedIn profile?

Research Question 2: What is the relationship between the way candidates shape their professional profile on LinkedIn and their professional performance?

In addition, just as not all curriculum vitae use the same approach and there are differences depending on the industry or sector, different professional profiles also differ in how they use LinkedIn. For instance, there are differences in the number of average contacts, in spelling errors, in the number of recommendations received and sent, and in the amount of personal information that is revealed (Zide et al., 2014). In fact, this information is relevant since recruiters take it into account when they evaluate a LinkedIn profile. Various studies have analysed how there are cultural differences in the way recruiters analyse this information (Caers & Castelyns, 2011). This implies that the same evaluation criteria should not be de facto used independently of the sector and the professional profile in which the selection process is contextualized. However, to the best of our knowledge, no studies have analysed how the information contained in the profiles of ICT professionals relates to professional performance. Therefore, the analysis of the degree to which the design of the LinkedIn profile of ICT professionals varies according to aspects such as professional experience, gender, or place of residence is of interest to interpret the information. In this sense, we propose the following research question:

Research Question 3: Does the design of ICT professionals profile vary based on their professional experience, gender, or geographical location?

In summary, despite the intense use of LinkedIn as a selection tool, there are few empirical studies about it (Roth et al., 2016; McFarland & Ployhart, 2015). Our study aims to contribute to determining how to process the information contained in LinkedIn profiles and the connection of this information with job performance in a context that is also highly relevant for the socio-economic development, such as that of ICT professionals. In line with the above, the objective of our work is to obtain initial evidence of the validity of the information contained in LinkedIn profiles of ICT professionals for decision making in personnel selection contexts. This is important from both academic and applied points of view. On the one hand, it allows conducting a guided analysis of LinkedIn profiles taking into account those elements that are related to professional performance. On the other hand, it offers valuable knowledge regarding the usefulness of the information contained in LinkedIn profiles of ICT professionals in the context of personnel selection.

Method

Participants

A total number of 615 ICT professionals, all from the same company, participated in the study. Of these, 26.38% were women. The age ranged from 21 to 61 (mean = 35.51, *SD* = 6.74). The participants had different professional roles. Junior roles: software developer-programmer (77.7%), analyst programmer (2.3%), and junior consultant (1.6%). Senior roles: analyst (7%), solution architect (0.1%), consultant (5.8%), senior consultant (2.6%), project manager (2.5%), and project director (0.5%). They were located in 12 Spanish provinces, 61% lived in small provincial cities (e.g., Salamanca, Cáceres) and 39% in large cities (Madrid, Barcelona, or Valencia). Regarding their contract situation, 72% of the participants had an open-ended contract. Participants voluntarily consented to participate in the study and the human resources committee of the organization authorized it.

Measures

LinkedIn measures. Table 1 shows the measures taken from participants' LinkedIn profiles. Following the strategy employed by Zide et al. (2014), to identify the most important LinkedIn variables for the ICT profile recruiters we carried out a set of semi-structured interviews with a convenience sample of HR professionals. The sample included two consultants specialized in ICT profile recruitment and a consultant specialized in social media. After the interviews, a set of 75 LinkedIn variables were identified that could be coded for further analysis. Of these, after conducting a focus group with the interviewees, we selected the 21 variables that appear in Table 1 to use in the study. The focus group followed the usual standards (Barbour, 2008; Kitzinger & Barbour, 1999; Morgan, 1988). The focus group is an informal dialogue between group members and a facilitator who directs and guides the discussion (Packer-Muti, 2010). Following the suggestion made by Krueger (1994), we used a "mini group" composed of the three experts with whom the interviews were held. In addition, one researcher with experience in focus groups carried out the facilitation tasks together with a research assistant who collected the generated information. There was a single session with a duration of 80 minutes. The session was not recorded for further analysis. At the beginning of the session, the facilitator presented the objectives, and we understood that the information was saturated when the members of the group reached an agreement on the variables to be included in the analysis.

Performance measures. The following measures were taken to assess the incumbents' organizational activity:

Productivity indicates the percentage of hours (with respect to the 1,880 hours per year set out in the collective agreement for the sector) of each participant that are productive for the organization (this includes hours that the client can be billed for, the hours dedicated to internal contracts, hours dedicated to preparing proposals for clients, and hours devoted to internal activities related to improving effectiveness).

Overall assessment of performance indicates the general assessment the supervisor makes of each employee annually about the contribution they make through their behaviour. The assessment is made according to two items. In the first, each supervisor indicates the overall contribution made by the employee in a four points Likert scale (from 1 - *poor contribution*, to 4 - *extraordinary contribution*). In the second, the evaluator assesses the difference between the number of competences in which the evaluated person shows strengths and the number of competences in which the evaluated person shows weaknesses. To be able to the addition of the two items, this second is recoded on a scale of 4 points from the cut-off points that mark the quartiles. In both items the supervisor takes into account the employee's behaviour in eight required competencies (teamwork, communication, flexibility, planning and organization, creativity and innovation, resolution and management of work, orientation to the client, and identification and commitment to the organization). The reliability, Cronbach's alpha, of this measure obtained was .50.

Potential for professional development: this is the estimate the supervisor makes of the employee's potential for developing their career in the commercial, technical and people management areas on a Likert scale of four points (0 - *no potential*, 1- *low potential*, 2 - *potential that can be developed*, 3 - *high potential*). As the measurement of each potential was obtained through a single item, no reliability measures could be determined.

Absenteeism: this was estimated from the percentage of hours (with respect to the 1,880 annual hours established in the collective agreement of the sector) that each employee reports as an unjustified absence from their job. Absences due to holidays, sick leave, or maternity/paternity leave were not taken into account.

Procedure

The data were collected from the LinkedIn social network between December 2016 and February 2017. Three members of the research team obtained the participants' profiles from LinkedIn through a Premium-Recruiter profile. The profiles were printed so they could be analysed in a static way at a specific point in time. The researchers analysed the content of the profiles according to the 21 target variables (Table 1). The performance measures were obtained from the Human Resources Information System of the organization that participated in the study. More specifically, productivity and absenteeism were extracted from the management and reporting control module, while the overall assessment of performance and potential for professional development estimates were obtained from the performance management module. The data were obtained in collaboration with the technical staff of the organization's information systems.

Table 1. Variables in the Study. Descriptive Statistics for Original and Recoded Values

	Variable name	Min.	Max.	*M*	*SD*	Recoded	M_r	SD_r
	LinkedIn measures							
1	Presence of photo False (1) - True (2)	1	2	1.65	0.48			
2	Contacts Number of contacts shown in the profile[1]	0	500	141.87	115.69	1-10	5.47	2.88
3	Contact Sources Number of contact sources available in the profile.	0	5	0.24	0.65	1-2	1.16	0.37
4	Categories filled in Number of categories filled in the profile to show the user information	2	15	6.50	2.40	1-5	2.76	1.42
5	Length of the extract Number of lines in the extract	0	32	1.95	4.18	1-2	1.30	0.46
6	Work experience Number of work experiences shown in the profile	1	27	3.96	2.78	1-5	3.19	1.35
7	Employment roles Number of employment roles shown in the profile	1	13	3.22	2.01	1-5	2.85	1.30
8	Length of the description of experience Number of lines in the description of experience	2	337	27.41	29.67	1-10	5.42	2.88
9	Companies indicated Number of companies for which the user indicates that he/she have worked	1	11	3.05	1.86	1-5	2.75	1.29
10	Extent of experience Number of months that add up all the experiences indicated.	15	524	146.15	81.96	1-10	5.47	2.87
11	Charity causes identified Number of charitable causes that the user indicates in their profile	0	14	0.57	1.82	1-2	1.13	0.34
12	University education Number of official university education (grade or post-graduate) indicated by the user	0	5	1.15	0.81	1-5	2.12	0.77
13	Additional training[2] Number of additional courses to the regulated university education indicated by the user	0	45	2.13	5.23	1-2	1.80	0.40
14	Validated aptitudes Number of validations of all the skills of the profile	0	579	51.26	67.29	1-5	2.97	1.43
15	Recommendations received Number of recommendations received	0	15	0.32	1.24	1-2	1.14	0.35
16	News followed Number of news followed	0	23	0.93	2.05	1-2	1.47	0.50
17	Universities followed Number of universities followed	0	17	0.94	1.01	1-2	1.72	0.45
18	Groups followed Number of groups followed	0	54	4.38	6.80	1-5	2.73	1.55
19	Companies followed Number of companies followed	0	647	11.10	34.52	1-5	2.96	1.17
20	Interests identified Number of interests identifies by the user	0	14	0.66	2.03	1-2	1.13	0.33
21	Languages indicated Number of languages indicated by the user	0	4	0.79	0.93	1-5	1.76	0.89
	Performance measures							
22	Productivity	0	99.4	88.10	10.40	1-10	2.49	1.12
23	Overall assessment of performance	2.0	8.0	5.29	1.59			
24	Potential for professional development: commercial area	0	3.0	0.10	0.50			
25	Potential for professional development: people management area	0	3.0	0.70	1.10			
26	Potential for professional development: technical area	0	3.0	1.60	1.00			
27	Absenteeism	0	17.3	2.90	2.10	1-4	2.50	1.13

Note. [1]On LinkedIn even if an user has more than 500 contacts, this is the limit that is shown so the scale is truncated in this number; [2]due to negative loadings in the factorial analysis this variable was recoded reversely (1 = user identifies one or more additional training, 2 = user identifies no additional training) in order to simplify the explanation of the results; min. = minimum; max. = maximum; *M* = mean; *SD* = standard deviation; recoded = categories in which the original data has been recoded; M_r = mean of the recoded score; SD_r = standard deviation of the recoded score; in blanks variables not recoded.

Table 2. LinkedIn and Performance Measures Inter-correlations (Recoded Variables)

		2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1	LI 1	.38	.16	.37	.23	.14	.16	.22	.10		.11	.14		.36	.11	.23	.15	.24	.31	.20	.24	.09					
2	LI 2		.32	.48	.27	.40	.40	.39	.37		.08	.27		.63	.29	.44	.18	.58	.51	.22	.19	.18		.08	.12	-.12	
3	LI 3			.31	.21	.14	.19	.16	.13		.10	.09		.25	.18	.18	.10	.30	.27	.20	.11			.	.11	-.11	
4	LI 4				.54	.29	.33	.37	.27	-.09	.34	.27		.56	.27	.41	.21	.53	.53	.46	.56	.11					
5	LI 5					.22	.21	.30	.21	.09	.14	.09		.28	.21	.23	.10	.39	.30	.27	.23			.09			
6	LI 6						.88	.81	.82	.37		.20		.32	.21	.22	.11	.29	.27	.09	.18			.12	.11	-.15	
7	LI 7							.73	.75	.36		.22		.34	.24	.24	.12	.31	.30	.13	.20			.13	.15	-.14	
8	LI 8								.66	.30	.10	.17		.35	.27	.23	.13	.30	.30	.17	.21						
9	LI 9									.32		.17		.30	.19	.26		.28	.30	.11	.19	.11				-.14	
10	LI 10												.08											.19	.27	-.18	
11	LI 11													.14	.08	.10		.12	.18	.21	.19						
12	LI 12												.24	.20		.27	.54	.18	.33	.12	.12	.09			.08		
13	LI 13																.19										
14	LI 14														.30	.38	.14	.45	.48	.26	.32	.19					
15	LI 15															.18		.26	.24	.14	.					-.12	
16	LI 16																.25	.45	.70	.17	.21	.15					
17	LI 17																	.14	.38	.11	.09						
18	LI 18																		.56	.23	.23	.17					
19	LI 19																			.24	.27	.23				-.10	
20	LI 20																				.26						
21	LI 21																					.08			-.08		
22	Pf. 1																										-.43
23	Pf. 2																								.26	.17	
24	Pf. 3																								.13	-.18	
25	Pf. 4																									-.28	
26	Pf. 5																										.08
27	Pf. 6																										

Note. For legilibility we omit non-significant correlations and all correlations showed are significant ($p < .01$) except those shown in *italics* ($p < .05$); LI 1, LinkedIn 1 = presence of photo; LI 2 = LinkedIn 2 contacts; LI 3 = LinkedIn 3-contact sources; LI 4 = LinkedIn 4-categories filled in; LI 5 = LinkedIn 5-length of the extract; LI 6 = LinkedIn 6-work experience; LI 7 = LinkedIn 7-employment roles; LI 8 = LinkedIn 8-length of the description of experience; LI 9 = LinkedIn 9-companies indicated ; LI 10 = LinkedIn 10-extent of experience; LI 11 = LinkedIn 11-charity causes identified ; LI 12 = LinkedIn 12-university education; LI 13 = LinkedIn 13-additional training; LI 14 = LinkedIn 14-validated aptitudes; LI 15 = LinkedIn 15-recommendations received; LI 16 = LinkedIn 16-news followed; LI 17 = LinkedIn 17-universities followed; LI 18 = LinkedIn 18-groups followed; LI 19 = LinkedIn 19-companies followed; LI 20 = LinkedIn 20-interests identified; LI 21 = LinkedIn 21-languages indicated; Pf 1 = productivity; Pf 2 = overall assessment of performance; Pf 3 = potential for professional development: commercial area; Pf 4 = potential for professional development: people management area; Pf 5 = potential for professional development: technical area; Pf 6 = absenteeism.

Results

Descriptive Analysis

The descriptive analysis of the collected LinkedIn variables showed that the value range of each variable differed greatly. Therefore, with the aim of providing common scales to understand the different variables, they were transformed into scales of 10, 5, and 2 points. The variables that showed the largest range of scores, contacts (V2), length of the description of experience (V8), and extent of experience (V10) were transformed into a 10-point Likert scale taking their percentiles as cut-off points. The number of categories filled in (V4), work experience (V6), employment roles (V7), companies indicated (V9), university educational community (V12), and validated aptitudes (V14) variables showed less data dispersion and were transformed into a 5-point scale taking the values of their quintiles as cut-off points. The distribution of the rest of the variables had a high percentage of responses in a single category, so they were easier to understand in terms of the presence or absence of that element in the LinkedIn profile. Therefore, the contact sources (V3), length of the extract (V5), charitable causes indicated (V11), additional training (V13), recommendations received (V15), news followed (V16), and universities followed (V17) variables were transformed into variables with two categories. The first category indicates that there is no information about the variable in the user's profile and the second indicates that there is information about the variable in the user's profile. The presence of photo (V1) variable was not transformed because it was already in an absence-presence scale. Similarly, the performance measures expressed in percentages of hours (productivity and absenteeism) were also recoded into ten and four-point scales respectively according to the cut-off points that marked their respective percentiles (productivity) and quartiles (absenteeism). Table 1 shows the descriptive statistics of the variables used in the study and Table 2 shows their inter-correlations.

Photography is present in just over two-thirds of the profiles in the sample. The number of participants' contacts is not very high (a little less than 142 on average, compared to the maximum limit of 500 established by the platform). Not much contact information was included (average 0.24), which may be because the platform is considered a contact source in itself. As for the reported experience, the average is nearly 4 experiences (3.96) and the number of companies in which the person has worked is just over 3 (3.05), which is consistent with the rotation that exists in the sector (LinkedIn, 2018). Significantly, the number of validated aptitudes in the profile (mean of 51.26) is consistent with the technological component of ICT professionals and the great wealth of knowledge and technologies in the sector. However, these professionals often do not receive recommendations (mean of 0.32).

The data on performance measures showed that the percentage of average effective hours is 88.1%, with a standard deviation of 10.4. The overall performance has a mean of 5.29 and a standard deviation of 1.59. The technological potential reached a higher mean (1.6), consistent with the sample characteristics, although participants scored lower on their potential for managing people (average 0.7) and their potential towards the commercial area (average 0.1).

Dimensionality

An exploratory factor analysis was carried out to explore the underlying dimensionality of the information present in the LinkedIn profile. The previous analyses showed the adequacy of the data to proceed to the factorial analysis (KMO = .856, Bartlett's test, $p < .001$). Following the recommendations provided by Flora, LaBrish, and Chalmers (2012) the unweighted least square (ULS) method (Joreskög, 1977) was used to estimate parameters. ULS has been seen as adequate when dealing with Likert polytomous responses in a continuum measure construct (e.g., Castaño & García-Izquierdo, 2018), and offers robust solutions especially if the number of factors to be retained is small (Jung, 2013). We developed the analysis using FACTOR (Lorenzo-Seva & Ferrando, 2006). The parallel analysis determined four factors that together explained 55.2% of the variance. To interpret the factors both orthogonal and oblique rotations were carried out, which quickly converged into five and seven iterations, respectively. The factorial solutions rotated in both cases yielded identical associations between the variables and the factors, with small differences in the factorial saturations and in the order of the factors.

To facilitate the visualization of the factorial structure, Table 3 shows the oblique rotation obtained (Oblimin Method). As it can be seen, the first factor extracted is associated with work experience, employment roles, companies indicated, length of the description of experience, and extent of experience variables. These variables reflect the degree to which professional profile reflects a participant's "breadth of professional experience". The second factor extracted is associated with companies followed, contacts, news followed, groups followed, validated aptitudes, and recommendations received variables. These variables, taken together, show participants' intensity of interaction with the social network community. It should be noted that participants' activity in the network is dynamic. The factor could therefore be labelled as "breadth of interaction on LinkedIn", or "social capital". The third factor includes university education, universities followed, and additional training variables, which together reflect participants' academic interest in keeping up-to-date in the contents relevant for their professional activity. We could therefore label this third factor as "interest in updating knowledge". Finally, the fourth factor is associated with categories filled in, languages indicated, interests identified, charity causes identified and length of the extract variables. These variables refer to the degree to which a participant has completed their static profile (it does not particularly reflect a user's interaction with the profile over time), and denotes users' interest in providing a profile that is as complete as possible. We could label this fourth factor as "breadth of the non-professional information". The estimated reliability of the factors based on the Cronbach's alpha coefficient was found to be .97, .86, .73, and .98 respectively for factors 1, 2, 3, and 4.

Table 3. LinkedIn Variables Rotated Loading Matrix

	F1	F2	F3	F4
V6 Work experience	.99			
V7 Employment roles	.88			
V9 Companies indicated	.81			
V8 Length of the description of experience	.77			
V10 Extent of experience	.51			
V19 Companies followed		.76		
V2 Contacts		.76		
V16 News followed		.69		
V18 Groups followed		.67		
V14 Validated aptitudes		.53		
V15 Recommendations received		.31		
V12 University education			.75	
V17 Universities followed			.67	
V13 Additional training*			.37	
V4 Categories filled in				.95
V21 Languages indicated				.57
V20 Interests identified				.50
V11 Charity causes identified				.44
V5 Length of the extract				.40
V3 Contact sources				
V1 Presence of photo				

Note. Method for factor extraction: unweighted least squares (ULS); rotation to achieve factor simplicity: direct Oblimin; goodness of fit statistics (NNFI = .89, CFI = .93, GFI = .99, AGFI = .99, RMSR < .05); loadings lower than absolute .30 omitted.

Differences between Groups

The professional profiles were significantly different in relation to the degree of experience, gender, and province of work; however, they were not significantly different in relation to age. Table 4 shows the differences obtained with the ANOVA. The "junior" and "senior" groups differed significantly in the "breadth of professional experience" factor ($F = 32.5$, $p < .001$). The senior group had higher scores which is consistent with the greater experience that these professionals usually have. In the factor "breadth of interaction on LinkedIn" ($F = 3.58$, $p < .05$) the senior group also had higher scores

Table 4. Mean LinkedIn Factors Differences (ANOVA) by Seniority, Gender, and Geographical Location

	LinkedIn Factor 1: Breadth of professional experience	LinkedIn Factor 2: Social capital	LinkedIn Factor 3: Interest in updating knowledge	LinkedIn Factor 4: Breadth of the non-professional information
Junior (n = 502)	-.11	-.04	.02	.01
Senior (n = 113)	.47	.16	-.07	.01
F	32.50***	3.58*	0.73	.01
Women (n = 162)	-.01	.06	-.04	.07
Men (n = 453)	.02	-.18	.10	-.19
F	0.06	7.32*	2.38	7.77*
1. Large cities (n = 240)	.15	-.06	-.08	-.08
2. Small cities (n = 375)	-.10	.04	.05	.05
F	9.32***	0.24	2.56	2.58

*$p < .05$, ***$p < .001$.

than the junior group. Significant differences were found in relation to gender in the “breath of interaction on LinkedIn” factor (F = 7.32, $p < .05$), as women scored higher than men, and in the “breadth of non-professional information” factor (F = 7.77, $p < .05$) women scored higher than men. There were significant differences in relation to the geographical location where a professional works (F = 9.32, $p < .001$) in factor 1, “breadth of professional experience”, as there was a greater breadth of professional experience in large cities versus small cities.

Validity

Table 5 shows the correlations between LinkedIn factors and performance measures. Correlations corrected by attenuation are shown in brackets (Muchinsky, 1996). We use the single correction due to unreliability of factor scores. Corrected correlations are discussed below. It can be seen that breadth of professional experience (factor 1) shows a significant relationship in the group of junior participants with commercial potential (r_{xy} = .13, $p < .001$), people management potential (r_{xy} = .18, $p < .001$), and technological potential (r_{xy} = -.18, $p < .001$). In the senior sample this factor shows a significant correlation with absenteeism (r_{xy} = .18, $p < .05$). Social capital (factor 2) in junior participants shows a significant relationship with productivity (r_{xy} = .27, $p < .001$), absenteeism (r_{xy} = -.17, $p < .001$), and technological potential (r_{xy} = -.11, $p < .05$). Interest in updating knowledge (factor 3) shows a significant correlation in junior participants with productivity (r_{xy} = .12, $p < .05$). Finally, breadth of non-professional Interest in updating knowledge (factor 4) correlates significantly with productivity (r_{xy} = .17, $p < .001$) in the junior sample and with absenteeism in the senior sample (r_{xy} = .24, $p < .05$).

In line with the above, various regression analyses were carried out to deepen the analysis of the relationships found. The stepwise method was used. The four factors were used as independent variables and each of the criteria measured (productivity, general performance, commercial potential, potential for people management, technological potential, and absenteeism) were used as dependent variables. For the sample of junior participants, significant models were found for productivity (R = .27, $p < .001$) with the score in factor 2; for potential for managing people (R = .26, $p < .001$) with the score in factors 1 and 4 (beta = -.25, $p < .001$; beta = -.20, $p < .001$, respectively); for technological potential (R = .18, $p < .001$) with the score in factor 1; for commercial potential (R = .13, $p < .05$) with the score in factor 1; and for absenteeism (R = .15, $p < .001$) with the score in factor 2. For senior participants, only one significant model was obtained: for absenteeism (R = .24, $p < .05$) with the score in factor 4.

Discussion

The present work examined the relationship between the information contained in LinkedIn profiles of ICT professionals and their professional performance. To do this, firstly, the dimensionality of the variables studied in LinkedIn profiles was analysed, which showed that four factors explain 55.2% of the common variance of variables. These factors are labelled as: breadth of professional experience (factor 1), breadth of interaction on LinkedIn or social capital (factor 2), interest in updating knowledge (factor 3), and breadth of non-professional information (factor 4). Our study showed significant differences in LinkedIn profiles of ICT professionals in relation to professional experience, gender, and a professional’s location; however, there were no significant differences in relation to age. Most experienced professionals have a greater breadth of professional experience and a greater breadth of interaction on LinkedIn than less experienced professionals. Women report a greater breadth of interaction on LinkedIn and a greater breadth of non-professional information in their profiles than men. Professionals located in large cities have a greater breadth of professional experience than professionals located in smaller areas. These results have implications in theoretical and practical areas that we discuss now. Our study is a first step forward in the exploration of the relationships between LinkedIn profiles and job results and performances. Our results show that breadth of interaction on LinkedIn in junior participants relates to their job results (effective hours), their potential for managing people, and their hours absent. Hence, the greater the professional breadth of interaction on LinkedIn, the greater the job results obtained by an organization, productivity, through the sale of professionals’ effective hours of work. However, the greater this interaction, the lower both the estimate of a professional’s management potential and hours absent. Breath of professional experience also in the junior participants relates to the estimation of both their commercial and technological potential. In both cases, the greater the breadth of professional experience reported by the professional in his/her LinkedIn profile, the greater the estimate of their commercial and technological potential. We can state here that work experience has

Table 5. Correlation between LinkedIn Factors and Performance Measures

		1	2	3	4	5	6	7	8	9	10
1	LinkedIn Factor 1: Breadth of professional experience	*.97*	.43**	.14**	.31**	.02	.13**	.18**	-.18**	.08	-.02
2	LinkedIn Factor 2: Social capital	.35**	*.86*	.35**	.65**	.02	.03	.02	-.10* (-.11**)	.27** (.29**)	-.15** (-.17**)
3	LinkedIn Factor 3: Interest in updating knowledge	.14**	.35**	*.73*	.20**	.06	.06	.08	-.06	.10* (.12**)	-.05
4	LinkedIn Factor 4: Breadth of the non-professional information	.35**	.53**	.25**	*.98*	-.06	.05	-.12	-.04	.17**	-.09
5	Performance overall assessment	-.09	-.03	-.09	.02	*.50*	.06	.25**	.12**	.02	-.01
6	Potential for professional development: Commercial area	.04	.01	-.01	-.01	.04	s.i.	.20**	-.23**	.07	-.09*
7	Potential for professional development: People management area	-.07	.01	-.06	.05	.27**	-.05	s.i.	-.31**	-.03	-.02
8	Potential for professional development: Technical area	-.07	-.07	.03	.08	.34**	-.07	-.14	s.i.	-.08	.09*
9	Productivity	.14	.07	-.01	-.08	.12	-.06	.08	.03	s.i.	-.46**
10	Absenteeism	.18*	.15	-.05	.24*	.03	-.06	.03	.04	-.25	s.i.

Note. Junior participants (n = 502) above diagonal and senior participants under diagonal (n = 113); between brackets single correction for attenuation due to factor reliability (only show in case that correction correlation was different from observed correlation); reliability estimation in italics in principal diagonal; s.i. = single item, no reliability estimated.
*$p < .05$, **$p < .001$.

been a traditional topic in personnel selection and validation, where research has demonstrated its validity consistently. For instance, the classical meta-analysis by McDaniel, Schmidt, and Hunter (1988) presented a mean correlation of .32, although Quiñones, Ford, and Teachout (1995) showed an estimated population mean of amount (M_ρ = .43) with measures of work experience. More recently, Van Iddekinge, Arnold, Frieder, and Roth (2018), have found overall small corrected correlations of .07 for job performance, more predictive when workers are newcomers and in less complex jobs.

Interest in updating knowledge in junior participants is related directly to their performance and inversely to the estimation of their potential for managing people. Finally, breadth of professional experience and breadth of non-professional information in the senior group is positively related to absenteeism.

The information contained in LinkedIn profiles has been analysed individually (see for example Zide et al., 2014), rather than trying to offer an overview of the content in the professional profile. However, our study shows that the information contained in these profiles can be summarized in four large blocks or factors. This grouping is theoretically and methodologically relevant since it makes it possible to use a smaller amount of information about profiles to study them in depth. It is noteworthy that these four factors have a broad transversality towards other professional profiles since, in fact, they do not consider the content of the profile but rather professionals' use of LinkedIn profile. That is, factors do not consider whether a professional has – for example, a certain and specific academic degree (e.g. Grade in Mathematics) –, but rather how many academic degrees he/she has. Making a parallel comparison with the personality study, is it possible that we are facing LinkedIn's Big Four?

On the other hand, as expected and as other studies have pointed out (Zide et al., 2014), professional profiles on LinkedIn vary in relation to gender and professional experience. In the case of gender, our findings point to how women obtain higher scores than men in social capital and breadth of non-professional information, which is no consistent with the results that men tend to be more active on LinkedIn than women (Nikolaou, 2014). The evidence indicates that HR professionals use non-professional information in profiles to assess person-organization fit (Bangerter, Roulin, & Konig, 2012; Roulin & Bangerter, 2013), and therefore this social capital factor is a relevant aspect that must be analysed.

The evidence that the senior group scored significantly higher than the junior group on factors related to professional experience (breadth of professional experience and breadth of interaction on LinkedIn) reports an evidence of the validity of factors found. Different studies have studied the relationship between age and use of social media, such as LinkedIn, obtaining contradictory results (e.g., Aguado et al., 2016; Davison et al., 2011). In our study, instead of using age, we have used experience, which, although reflects an age component, has a greater work implication and more flexible borders.

An additional value of our study are differences found in relation to the province in which the participants work. In large centres, such as Barcelona and Madrid, professionals have a greater breadth of professional experience, which could mean greater competitiveness to find a job in these centres and consequently the work experience of professionals located in large work centres is more developed.

Relationships found between the information contained in LinkedIn profiles and performance of ICT professionals show that there are individual differences in the use of these profiles that are related to main criteria of personnel management in the business field. The results of ICT professionals, in terms of effective hours of work sold by the organization, are mainly related to breath of interaction on LinkedIn. Thus, we can see this as the more an ICT professional develops his or her social capital in LinkedIn, the greater the percentages of effective work hours the organization will "sell" of this professional. In addition, an ICT professional's social capital is also inversely related to absenteeism; that is, the greater the social capital, the less time the professional is absent. This could be signalling a greater commitment and engagement of these professionals: LinkedIn is a professional network and the degree to which professionals develop their social capital in it can be taken as an indicator of their involvement with deepening the network built around the work they do. However, this dynamism in the use of LinkedIn is not related to the assessment of their professional performance. In other words, it does not seem that the intensity in the development of interactions on LinkedIn denotes the existence of special competencies (e.g., teamwork, communication, flexibility, or planning and organization) related to an ICT professional's performance. Therefore, it is not a relevant element of profiles. This contrasts with the usual practice in which a candidate with a greater number of contacts or with a greater number of validated aptitudes is better valued (Caers & Castelyns, 2014).This performance is related, but only weakly, to the interest in updating knowledge.

In line with what may seem reasonable, commercial potential and technological potential of ICT professionals are related to the breadth of professional experience shown in LinkedIn profile. The greater this professional experience, the greater the commercial potential and the lower the technological potential. In a field such as ICT, where technology develops at high speed, professionals with more experience are probably not as up-to-date in latest technologies as newcomers. And, on the contrary, their experience gives them a good background for commercial work.

In any case, relationships found between LinkedIn factors and criteria are different for junior and senior professionals. This clearly indicates that information presented in LinkedIn profiles has differential considerations according to the level of experience of ICT professionals. This inevitably leads to a differential consideration of this information by recruiters when it comes to selecting professionals with that degree of differential experience.

Our work also has interesting practical implications. It provides relevant knowledge of candidates in the ICT sector for both recruitment and selection professionals, as well as for the candidates themselves for making their experience visible through the LinkedIn profile. Regarding the former, our study offers professionals a first approach to connecting information contained in LinkedIn profiles with the predicted future job performance of a candidate. Our study provides evidence of what elements of those profiles are relevant to this objective, differentiating between junior and senior profiles. The descriptive information is of practical interest regarding the values obtained by ICT professionals in the different LinkedIn profile fields analysed. Thus, recruiters in the ICT sector can contrast values of a specific candidate in their profile compared to the average amounts we have found with a broad sample. In addition, this study opens the door to developing standardized instruments that allow the recruitment and selection to make normative interpretations of the information contained in professional profiles. To this end, automated systems and development of rubrics for assessing profiles could be interesting contributions for professional practice. However, automated systems enter the thorny issue of artificial intelligence and the automated analysis of information contained in profiles currently clashes with different administrative-legal limitations (e.g., data protection laws) and operational limitations (LinkedIn does not allow automated exploitation of information contained in profiles even though users have shared it openly and voluntarily). Nevertheless, rubrics supported by the study's findings and those of subsequent research would be a valuable tool for standardizing a process that, to date, is based more on a recruiter's experience than on an evaluation methodology.

Limitations of the Study and Future Research

Although the study provides valuable knowledge both at theoretical and practical level, it is not exempt from limitations that must be pointed out. First, we outline the limitations of LinkedIn variables selected for the study. Although we followed expert judgment to select profile variables, LinkedIn offers much more information than has been contemplated in the study, both in the variables used and in the quality of them. For example, of the 75 initially coded variables, only 21 were used in the study. It is necessary to point out that, although significant relationships have been found between LinkedIn profile and some of the performance variables considered, the effect size of correlations is not high. This indicates that it is necessary to include new and more variables in the study that reflect the use that ICT professionals make of their LinkedIn profiles.

In our study we have analysed LinkedIn profile information that can be quantified as “use” but we have not taken into account its content. Modern natural language processing techniques have proven to be effective in predicting personality in other social networks, such as Facebook (Schwartz et al., 2013; Youyou, Kosinski, & Stillwell, 2014), and also in developing artificial intelligence systems for recruitment and selection (Faliagka et al., 2014; Faliagka, Tsakalidis, & Tzimas, 2012)). Therefore, these techniques could be used, for example, to analyse how users present themselves in their profile (beyond counting the number of lines of the presentation, as we have done in this study). On the other hand, the exploration of the network of contacts of a LinkedIn profile user is another of the elements that should be considered to improve the information that is extracted from these profiles. The Organizational Network Analysis (ONA) has been successfully applied in the strategic management of human resources (Collins, & Clark, 2003) and in the study of performance of leaders and work teams (Mehra, Dixon, Brass, & Robertson, 2006). Using it in the characterization of a candidate’s profile would provide a fundamental view of LinkedIn profiles: their relative positioning in the network of contacts through measures of centrality, prestige, balance, or affiliations and groups (Wasserman & Faust, 1994).

In addition, we mentioned above the possibilities that natural language processing and the analysis of organizational and social networks introduce for analysing and evaluating texts that appear in the profile and their relations with other members of the network; however, in our study this aspect has not been contemplated. Therefore, new studies are needed to introduce more variables into profile analysis and make a qualitative and relational analysis of their content. This will undoubtedly result in a better understanding of professionals’ LinkedIn profiles, and also in a greater predictive use of this information. Another limitation of the study is related to the sample of participants used. Although it has an adequate size, all participants came from the same organization, which may limit the possibilities of generalizing the results obtained. Further studies must be carried out to research generalizability of findings presented here both through studies with ICT professionals belonging to different organizations in the sector and through the use of other professional profiles. These two questions should orientate us on how cross-sectional factors found in our study are, and consequently the degree to which the factors make it possible to summarize the information contained in other professional LinkedIn profiles.

Although in our study we have objective measures of employee productivity and absenteeism, measures of reliability of overall performance and potential for professional development is a limitation. The former due to its low reliability and the latter because there are single item measures. When carrying out the research in a specific company that has its own systems, it was not possible to implement new performance measures. Further studies should contemplate this issue and analyse LinkedIn features in light of more reliable performance measures.

Moreover, we acknowledge this study suffer from range restriction as all the participants come from a single company. This leads us to think validity could be higher than results we have obtained here.

A final limitation that must be considered is the convergent nature of the study. LinkedIn profile data and participants’ results are taken in a convergent manner at a specific time. However, it is known that LinkedIn profile is something alive that users are feeding that varies over time. In this respect differences can be found in profiles depending on aspects such as whether a participant is actively job seeking or not. Subsequent studies should include this dynamism of both, LinkedIn profiles and longitudinal view, that reflects workers’ professional career from the time they are candidates and as they develop professionally in one or various organizations.

Conflict of Interest

The authors of this article declare no conflict of interest.

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