Journal of Work and Organizational Psychology (2023) 39(2) 75-88

Journal of Work and Organizational Psychology

https://journals.copmadrid.org/jwop

Big Four LinkedIn Dimensions: Signals of Soft Skills?

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ARTICLE INFO

Article history:
Received 25 February 2023
Accepted 12 June 2023

Keywords:
LinkedIn Big Four model
Soft skills
Signalling theory
Recruitment and selection

A B S T R A C T

The use of LinkedIn as a tool in the recruitment and selection process has become routine in human resource management. However, a major drawback of such an approach is the lack of systematic and rigorous inferences on the psychological characteristics of the candidates. Calls have been made by scholars for further research on the psychometric guarantee of LinkedIn as a tool in the selection process. This study adopts signalling theory as a framework for exploring how LinkedIn profile information signals a candidate's soft skills. Using a sample of 169 ITC professionals, through a cross-sectional design, soft skills were measured by means of a self-report questionnaire and LinkedIn profiles were assessed using rubrics for measuring the LinkedIn Big Four. Our findings demonstrate that LinkedIn Big Four Breadth of Professional Experience and Social Capital are valid signals of leadership, communication, problem solving, entrepreneurial and commercial thinking, planning and organization, and teamwork. We discuss the practical and theoretical implications of our results.

¿Son señales de *soft skills* las dimensiones del modelo LinkedIn Big Four?

Palabras clave:
Modelo LinkedIn Big Four
Soft skills
Teoría de las señales
Reclutamiento y selección

R E S U M E N

El uso de LinkedIn como herramienta en el proceso de reclutamiento y selección se ha convertido en algo habitual en la gestión de recursos humanos. Sin embargo, se carece de información rigurosa sobre la calidad de las inferencias que realizan los evaluadores sobre las características psicológicas de los candidatos, por lo que es necesario realizar más investigación sobre las garantías psicométricas de LinkedIn como herramienta de selección de personal. En consecuencia, el presente estudio adopta la teoría de las señales como marco para explorar cómo la información del perfil de LinkedIn es un indicador válido de las *soft skills* de los candidatos. Utilizando una muestra de 169 profesionales del sector tecnológico en España, mediante un diseño transversal, se midieron estas "habilidades blandas" a través de un cuestionario, mientras que los perfiles de LinkedIn se evaluaron utilizando las rúbricas del modelo LinkedIn Big Four. Los resultados muestran que las dimensiones del LinkedIn Big Four referentes a la experiencia profesional y el capital social, son señales válidas de las siguientes *soft skills:* liderazgo, comunicación, resolución de problemas, intraemprendimiento, pensamiento comercial, planificación y organización y trabajo en equipo. Finalmente, se discuten las implicaciones prácticas y teóricas de nuestros resultados.

Organizational success is influenced by the behavioural patterns developed by employees (Aguinis & O'Boyle, 2014). Identifying and selecting candidates with better job and organizational fit (e.g., Cable & Edwards, 2004) is therefore critical (Stemler et al., 2016). The quality of recruitment and selection processes depends on attracting a sufficient number of suitable candidates. Technology now plays a fundamental role in this area (García-Izquierdo et al., 2019; Ryan & Derous, 2019). Organizations are adopting e-recruitment and online assessment as key practices in adapting selection processes to an increasingly global and demanding context (Derous & De Fruyt, 2016). This adaptation is linked to the emergence of social network websites (SNW), which now figure prominently in staff planning processes due to their ability to connect people from around the world (Chapman & Mayers, 2015) and facilitate the employer/job candidate search process (Black & Johnson, 2012).

Despite its popularity, the use of SNW in recruitment and selection processes is not exempt from criticism. This criticism is mainly focused on the accuracy of inferences made by human resource professionals about the psychological characteristics of the candidates from the information contained in their SNW profiles (Kluemper et al., 2012; Roulin & Bangerter, 2013) and the subsequent decisions made with regards to job and organizational fit (Chamorro-Premuzic & Steinmetz, 2013). This decision-making process may be easily restricted by a lack of standardized measures, low reliability

Cite this article as: Andrés, J. C., Aguado, D., & García-Izquierdo, A. L. (2023). Big four linkedin dimensions: Signals of soft skills? *Journal of Work and Organizational Psychology, 39*(2), 75-88. https://doi.org/10.5093/jwop2023a9

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and scant evidence of validity (e.g., Cubrich et al., 2021; Van Iddekinge et al., 2016; Zhang et al., 2020).

The most frequently used professional SNW is almost certainly LinkedIn (Aguado et al., 2016), used by 87% of recruiters (Jobvite, 2019). Indeed, recent years have seen a significant increase in research on LinkedIn as a recruitment and selection tool (e.g., Roulin & Levashina, 2019). To address the aforementioned drawbacks, research on LinkedIn has focused on how human resources professionals use LinkedIn profiles in the selection process (e.g., Roth et al., 2016), and the way candidates optimize their profiles to obtain a position in the labour market (e.g., Guillory & Hancock, 2012). However, with the exception of the study by Roulin and Levashina (2019), we have found gaps regarding the psychometric properties of LinkedIn as an assessment tool. Little is known about which LinkedIn-related information is instructive about a candidate's individual features and which data can be accurately used to make inferences about the degree of fit between candidate profiles and the job and/or organization. Recent studies have attempted to answer these questions within the framework of the signalling theory (Fernandez et al. 2021). Signalling theory (Spence, 1973; Zahavi, 1975) offers a promising theoretical framework for understanding human resource management processes (Bangerter et al., 2012; Guest et al., 2021) and individual behaviour on SNW (e.g., Fernandez et al., 2021; Folger et al., 2022). Signalling theory addresses communication processes by focusing on the role of the signaller, the signal, and the receiver (Guest et al., 2021). For example, candidates (signallers) configure and share information in their LinkedIn profile (signals), which recruiters (receivers) interpret to infer individual psychological characteristics and make decisions. The signalling theory is based on the notion that the signals used by the signallers do not provide directly observable information about the signallers' characteristics.

Building on signalling theory to explore the use of LinkedIn as a selection tool, this study is based on two main premises. First, we argue that jobseekers' LinkedIn profiles signal individual characteristics through the display of a number of specific LinkedIn indicators, and that human resource professionals make inferences about candidates based on the information posted on applicant LinkedIn profiles (e.g., Caers & Castelyns, 2011). Second, we focus on a set of individual characteristics that can be framed as soft skills, and their relationship with LinkedIn content, with a view to contributing to research on selection predictors from a signalling theory perspective (e.g., Fernandez et al., 2021; Gosling et al., 2011; Van de Ven et al., 2017).

This study contributes to the understanding of LinkedIn usage along two main trajectories. First, we provide evidence as to which soft skills can be inferred through LinkedIn profiles. Second, we examine the degree to which LinkedIn profiles express individual differences between candidates, with particular focus on theoretical constructs related to job fit (Bohnert & Ross, 2010). Our study will therefore contribute to evidence about the validity and utility of LinkedIn as a selection tool.

The primary aim of this paper is to answer the following question: Is LinkedIn profile information a valid signal of soft skills? To this end, we used the LinkedIn Big Four model (Aguado et al., 2019) and an adaptation of the soft skills set used in the LinkedIn research conducted by Roulin and Levashina (2019).

Theoretical Framework

SNW as a Recruitment & Selection Tool

Recent decades have seen a rapid increase in the use of online recruitment (Pfieffelmann et al., 2010), which enables employers to attract and search for candidates in an easier, quicker, and more cost-effective way. Most jobseekers and HR professionals use SNW at the current time (Nikolaou, 2014; Woods et al, 2020).

For organizations, the main advantages of online recruitment are as follows: a) candidates can apply quickly; (b) high-quality information about candidates' specific competencies, skills and experience; (c) savings in both cost and time invested; (d) expressing the brand image the organization offers to candidates; (e) increased ability to reach a larger and more varied number of candidates; (f) employers are enabled to approach candidates who are not actively seeking a job (e.g., Galanaki, 2002; García-Izquierdo et al., 2015; Khlebarodava & Remeikiene, 2019; Lievens & Harris, 2003; Nikolaou, 2014).

For candidates, the main advantages of social networks are as follows: (a) the immediacy of the process holds high value (Nikolaou, 2014); (b) they enable multiple search and comparison of job offers while facilitating job application (Sylva & Mol, 2009); (c) rapid contact with a greater number of job offers (Lievens & Harris, 2003); (d) access to a greater flow of information about the vacancy and the organization (Galanaki, 2002). All these advantages facilitate the decision-making process and contribute to better and faster decisions (Kashi & Zheng, 2013).

In short, online recruitment has become firmly established as a fundamental strategy in the talent acquisition process (Derous & De Fruyt, 2016), offering benefits to both employers and candidates.

All the aforementioned advantages apply to the use of professional SNW as a recruitment tool, of which LinkedIn is a prime example. While the use of SNW in talent acquisition processes was initially limited to recruitment, their use has now spread to the assessment of candidate characteristics. The use of SNW has led to a blurring of the traditional distinction between recruitment and selection, as well as an increase in the use of LinkedIn as an assessment tool by HR professionals (Aguado et al., 2019).

However, the use of SNW in personnel selection can be problematic, largely due to the inferences made by HR professionals during profile analysis (Roth et al., 2016). Research suggests that recruitment and HR professionals can make inferences about internal characteristics of candidates (responsibility, emotional stability, and extraversion) from the information displayed by candidates on their LinkedIn profiles (e.g. Caers & Castelyns, 2011; van de Ven et al., 2017). However, as Roulin (2014) points out, the quality of these inferences is unclear and remains an unresolved issue.

Given that recruiters make inferences intuitively rather than through a systematic and evidence-based process when considering profiles (Shahani-Denning et al., 2017), it is crucial to address this aspect. Some studies also suggest that recruiters may exhibit bias in their use of information unrelated to job performance during the selection process (Brown & Vaughn, 2011; Purkiss et al., 2006). In other words, the use of some inappropriate signals may easily drive some recruiters to incorporate discriminatory elements that lead to biased decision making (García-Izquierdo et al., 2015). This may lead HR professionals to make long-term predictions about a candidate's performance or their likelihood to leave the organization based on these uncorroborated inferences (Roth et al., 2016). Fernandez et al (2021) found valid signals on LinkedIn for personality traits such as openness to experience, responsibility, extraversion, and agreeableness. However, Roulin and Levashina (2019) found no relationship between personality inferences and their self-reported assessment.

Given that LinkedIn can be considered a selection tool, there is an urgent need for research into psychometric characteristics such as reliability and validity (Aguado et al., 2016; Roulin & Levashina, 2019). As Kluemper et al. (2016) point out, although we know that HR professionals use LinkedIn to make initial screening decisions, there is little research on the methods used. Roulin and Levashina (2019) and Roulin and Stronach (2022), on the basis of the Realistic Accuracy Model (RAM), examine the convergent and predictive validity of LinkedIn profile information for making inferences about an individual's personality and skills, and subsequent recommendations with regard to the hiring of the candidate. Their findings show how inferences from a candidate's more visible skills (e.g., communication skills) are more meaningful than inferences from less visible skills (e.g. personality). In addition, Fernandez et al. (2021) used signalling theory to show how some specific indicators from LinkedIn profiles are valid signals for inferring an applicant's personality.

In short, the analysis of the correlations between LinkedIn user information and the usual predictors in the field of personnel selection (e.g. personality, skills) is a relevant line of research. Such analysis also requires the use of models that allow for a comprehensive understanding of LinkedIn profiles beyond the specific information they contain. The Big Four LinkedIn dimensions therefore offer a feasible alternative.

The Big Four LinkedIn Dimensions

LinkedIn contains biographic professional information (biodata) that can be easily disseminated via the Internet. Candidates can use LinkedIn to create a personal brand and social capital through the connection with other LinkedIn users (Cortez & Dastidar, 2022; McCabe, 2017). Users are able to manage and frequently update this information. LinkedIn profile information includes experience, projects, skills, languages, qualifications, publications, education, discussion and comments, recommendations, interests, awards, and contact information for other users (López-Carril et al., 2020; Paliszkiewics & Madra-Sawicka, 2016). As such, LinkedIn profiles can be considered as digital CVs (Kluemper, 2013; Zide et al., 2014) from which recruiters can attribute the psychological characteristics of an applicant. LinkedIn also provides information that is not available on traditional CVs. The number of connections can be used as an indicator of applicant networking skills, while skill endorsements offer a valuable indicator of level of experience (Roulin & Levashina, 2019). Given that CVs are known to play an extremely important role in the recruitment and selection process (Apers & Derous, 2017), these LinkedIn items also assume similar importance. An example is the way an appropriate photograph increases the likelihood that an organization will show interest in the profile (Brooks, 2019) and increases the perception of a candidate's credibility, social attractiveness, and competence (Edwards et al., 2015; Paliszkiewics & Madra-Sawicka, 2016). Recruiters infer a candidate's cognitive ability from the training, academic achievements, work experience, and qualifications detailed in the profile. Recruiters also infer potential professional success and the likelihood of leaving the organization from the number of job positions the candidate has occupied, and base inferences on future promotion prospects and job alignment on the candidate's academic degree (Brooks, 2019).

In addition, the creation of content in the Post-section demonstrates that the candidate is an active user of the social network and is keen to raise awareness of their profile (López-Carril et al., 2020). Candidates use the Interests section to join various online communities. Connecting with other groups with similar interests enables users to increase the likelihood of new job offers and business opportunities (Paliszkiewics & Madra-Sawicka, 2016). Contributions to online communities allow users to increase social exposure and demonstrate their leadership and coordination skills in the digital environment (Rangel, 2014). In the Recommendations section, candidates include the user recommendations sent or received. A recommendation is a reference written by another user (usually a boss, co-worker, subordinate, client, supplier, or professional), highlighting a candidate's skills, competencies, and knowledge (Paliszkiewics & Madra-Sawicka, 2016). These recommendations, which are equivalent to references or letters of recommendation, serve to confirm the reliability of the information contained in the professional profile and add to the attractiveness of the candidate (Peregrin, 2012).

Zide et al. (2014) identified 21 items that HR professionals usually take into account when evaluating LinkedIn profiles and making decisions (e.g., education, number of connections, profile completeness, profile photograph, recommendations, etc). A similar approach was taken by Chiang and Suen (2015), who identified 14 different components (e.g., experience, education, recommendations, and endorsed skills). Aguado et al. (2019) detected 21 elements in the ICT industry, organized into 8 different blocks (see Table 1). On the basis of these elements, and following a factorial strategy, the authors identified four LinkedIn big dimensions (LIBFD): breadth of professional experience, social capital, interest in keeping up-to-date knowledge, and breadth of non-professional information (Table 2), which explain 50% of the job performance variance of professionals in the ICT sector. The model proposed by Aguado et al. (2019) presents two interesting characteristics. First, it provides a more integrated view of a candidate's professional profile, using less information but with greater generalizability (4 dimensions versus 21 variables). Second, the four dimensions set out in the model are independent of the specific content of the LinkedIn profile. Instead of reflecting candidates' specific professional content (e.g., Degree in Sciences), they show candidates' use of LinkedIn as a tool to build their profile (e.g., LinkedIn profile completeness).

In this study, these LIBFD are used as characteristics that will be considered signals of a candidate's soft skills, for two main reasons. First, the assessment of global dimensions is more reliable than the assessment of facets (Ones & Viswesvaran, 1996). Second, the proposed LIBFD are based on the analysis of professional profiles in the field of ICT, a professional sector that is particularly active in the use of LinkedIn. The Information and Communication Technology industry occupies the first position in the "Top 10 LinkedIn Industry" ranking (21.7 million users in 2022, a 1.3 million increase compared to 2021), representing 4.7% of all LinkedIn users (Cruz, 2022). Various research studies on the use of LinkedIn use ICT as a reference (e.g., Aguado et al., 2019).

Soft Skills for Recruitment & Selection

It is well known that skills, together with the information contained in biodata (e.g. García-Izquierdo et al., 2020), are key variables in the recruitment and selection process. In addition to

Table 1. LinkedIn Profile Elements

Element	Description
Basic data	Picture; Name; Degree connection; Headline; Location; Connections; Contact info
About	Summary with key words
Experience	Description of the current and past professional experience with achievement goals
Activity	Posts, articles, comments or likes about articles posted by other LinkedIn members
Education and capacitation	Academic background; Courses; Licenses and qualifications; Skills and endorsements
Interests	Influencers; Companies; Groups; Schools
Accomplishments & Recommendations	Given and received recommendations; Publications; Projects
Volunteer experience and causes supported	Causes cared about and support for social welfare

hard skills, measures of soft skills are also relevant predictors of job performance and job fit for candidates. (Brown et al., 2004; Clarke, 2017; Heinsman et al., 2007; Mitchell et al., 2010; Sutton & Watson, 2013). We usually differentiate between hard skills (technical) – working with equipment, data, software – and intrapersonal soft skills – the ability to manage oneself –, and interpersonal soft skills – how one handles interactions with others (Laker & Powell, 2011). There is no clear definition of what soft skills are (e.g., Shalini, 2013), but for operational purposes, our study relies on the definition provided by Haselberger et al. (2012, p. 67): "Soft skills represent a dynamic combination of cognitive and meta-cognitive skills, interpersonal, intellectual, and practical skills. Soft skills help people to adapt and behave positively so that they can deal effectively with the challenges of their professional and everyday life."

Reports at an institutional level (European Commission [EC, 2012a, 2012b]) and some research in the field of human resources management (Grugulis & Vincent, 2009) demonstrate the way soft skills are closely related to employability. Some authors argue that soft skills make the difference for job applicants in every industry (Sutton, 2002).

While there is no consensus as to a definitive list of soft skills, various proposals have been made (e.g., Ahmed et al., 2015). Our study focuses on a set of skills previously used in studies exploring the validity of LinkedIn (Roulin & Levashina, 2019), which partially overlap with those used by Van Iddekinge et al. (2016).

To summarise, the importance of soft skills in recruitment and selection means that recruiters try to infer soft skills from the information contained in LinkedIn profiles and candidates try to reflect soft skills through the configuration of their profile. This communication process between recruiter and candidate can be usefully studied within the framework of the above mentioned signalling theory.

Connecting Theory and Models: Signals of Soft Skills in the LinkedIn Big Four Model

The signalling theory provides an interesting framework for studying behaviour on LinkedIn (Fernandez et al., 2021). This theory has been used to describe recruitment processes globally (Bangerter et al., 2012; Ruparel et al., 2022) and to explain specific aspects of the use of LinkedIn in such processes (e.g., Cubrich et al., 2021; Fernandez et al., 2021; Roulin & Bangerter, 2013; Stone et al., 2019). The basic idea of signalling theory is that the interaction process between two people (e.g., applicant and recruiter) consists of three basic elements: sender, receiver, and a set of signals that the sender issues to the receiver. These signals transmit the sender's unobservable characteristics (e.g., KSAOs), which the receiver can use in their interaction and communication with the sender when trying to reach an agreement. The selection process can therefore be understood as a process of negotiation between candidates and organizations (Derous & De Witte, 2001). The way the signalling theory can be used to study this process in a context of interactions between two parties with access to different and asymmetric information explains the interest in the signalling theory as a framework for the study of selection processes (Bangerter et al., 2012). During the selection process, hiring managers and applicants share information to analyse the fit between job and organization. (Roulin & Bangerter, 2013). In this process of information exchange, the recruiter and the candidate share information that is relevant to their interests (Bangerter et al., 2012; Herriot, 1989). For example, while recruiters will aim to accurately assess a candidate's future performance, candidates may not offer information about themselves if that information is not useful to their own particular objectives. As a result, and throughout the process, some signals will be informative of a candidate's characteristics and other signals will not.

To summarise, by analysing the selection process as a system of signals, we understand that it consists of: (a) a set of senders that generate various signals aimed at influencing the decisions made by the receivers (e.g., a set of candidates who develop their LinkedIn profile in order to be attractive to the labour market); (b) the acquisition of a set of skills necessary for professional performance, information that is not directly observable); and (c) a set of receivers of the information that interpret these signals as indicators of the unobservable characteristics of the senders (e.g., a recruiter who interprets the signal – the various jobs done throughout the candidate's career – as an indicator of the candidate's skills and characteristics).

One of the key issues in this process is the degree to which the signals emitted by the sender are truly informative of the unobservable characteristics sought by the receiver. To this end, the signals must have two fundamental characteristics: (a) they must be honest and adequately represent the candidate's characteristics (Bangerter et al., 2012) and (b) there must be evidence of a relationship between the explicit information expressed in the profile and the unobservable characteristic inferred (Ryan & Ployhart, 2014).

Regarding the first issue, the signals will be honest if they are difficult to fake by the candidates or when their emission implies a high cost for the issuer. Only those candidates who possess this characteristic will want to incur this cost (Bangerter et al., 2012). LinkedIn can be considered a valid vehicle for obtaining these honest signals, since the information contained in the platform is difficult to misrepresent and costly to produce (Fernandez et al., 2021). Information is hard to fake because the signals sent by the sender through LinkedIn usually correspond to objective facts related to the user's professional and academic career. Information is costly to produce because candidates must spend a great deal of time attaining such signals. Specific professional skills or university degrees are costly to acquire. LinkedIn profiles are also public. They can be viewed by current colleagues, supervisors, and friends. This means that posting false or inaccurate information can damage a candidate's reputation. We therefore expect LinkedIn to provide honest signals about a candidate's soft skills.

Regarding the second issue, researchers have found that signalling effectiveness is influenced by the characteristics of the receiver. The signalling process will be deficient if the receiver is unable to recognise the correct signals (Connelly et al., 2011). If the recruiter does not know which signals to use as indicators of unobservable candidate characteristics (e.g., soft skills), the signalling process will be impaired. On the basis of the signalling theory, we expect LIBFD to be signals that HR professionals can use as indicators of candidates' soft skills.

As the participants in this study deploy management skills in their various positions, we focus on a set of soft skills previously used in studies exploring the validity of LinkedIn (Roulin & Levashina, 2019; Van Iddekinge et al., 2016). These soft skills are also contemplated in the Great Eight Competencies Model (Bartram, 2005). Eight skills (leadership, planning, communication, teamwork, information seeking, problem solving, conflict management, and adaptability) were identified as the set of skills that managers use to successfully carry out their activity across a large number of jobs (e.g., Woo et al., 2008), and have been taken as a consensual reference. However, in the context of ICT, it seems appropriate to add a ninth soft skill taken from the same model (Entrepreneurial and Commercial Thinking), which various studies have established as a key skill for both internal and external entrepreneurship (e.g., Estrin et al., 2016), and is widely used by employers in various contexts (Accenture Universia 2007; Jung, 2015; Khairullina, et al., 2015). Table 2 shows a summary of the hypothesized signals.

Table 2. LinkedIn Big Four Dimensions, Soft Skills Used in the Study, and Hypothesized Signals

Variable Description	Hypothesized Signals	Confirmed
Soft Skills		
Leadership. Guides and motivates subordinates toward challenging work. Gives regular, specific and constructive feedback. Identifies the abilities of your subordinates to make the most of their worth.	LIBFD1 (H1a); LIBFD2 (H1b)	Yes
Planning & Organizing. Establishes the actions and resources necessary to achieve objectives. Make proper use of available resources. Establishes control and supervision mechanisms for the development of actions.	LIBFD4 (H2)	No
Communication. Expresses thoughts both verbally and non-verbally in a clear and appropriate way for interlocutors, either in group or individual interactions.	LIBFD2 (H3)	Yes
Teamwork. Creates and maintains team spirit. Understands the concerns and viewpoints of the people they work with. Offers help, advice and support when needed.	LIBFD2(H4a); LIBFD4 (H4b)	Partial
Problem Solving. Identifies problems and generates solutions to address them. Is capable of accessing extensive knowledge to find ways to solve a problem. Is capable of evaluating the output of a solution.	LIBFD2(H5a); LIBFD3(H5b)	Partial
Entrepreneurial and Commercial Thinking. Cares about own professional development. Remains alert to detect business opportunities and analyses them to assess the suitability of different lines of action.	LIBFD1(H6a); LIBFD2(H6b)	Yes
Information Seeking. Actively seeks information from different sources and identifies which is relevant for understanding and solving a given problem.	RQ1	NA
Conflict Management. Recognizes and adequately manages conflict, reaching solutions and maintaining interpersonal relationships.	RQ1	NA
Adaptability. Modifies the way they act in new situations. Accepts different points of view and is able to work effectively with different groups of people. Faces change positively and adequately manages the stress it produces.	RQ1	NA
LinkedIn Big Four Dimensions		
LIBFD1: Breadth of Professional Experience. Denotes the degree to which professional profiles reflect a participant's breadth of professional experience in terms of roles played, number of organizations in which the professional has worked and their temporal scope.	NA	NA
LIBFD2: Social Capital. Show candidates' intensity of interaction with the social network community.	NA	NA
LIBFD3: Interest in updating knowledge. Reflects participants' academic interest in keeping up-to-date in the content relevant for their professional activity.	NA	NA
LIBFD4: Non-Professional Information Amplitude. Refers the degree to which a participant has completed their static profile and denotes users' interest in providing a profile that is as complete as possible.	NA	NA

Note. LinkedIn Big Four dimensions and description was extracted from Aguado et al. (2019); NA = not applicable

Signals and Soft Skills: Leadership

The core elements of leadership skills include an individual's ability to manage and coordinate the actions of others, supervise the behaviour of employees and team members, delegate, offer coaching, empower, motivate, train employees, and identify and acquire talent. Several studies indicate that these leadership abilities are acquired through experience over a working career (Farr & Brazil, 2009; Lord & Hall, 2005; Mumford et al., 2000), particularly in job positions involving staff management. LIBFD1 (breadth of professional experience) reflects this candidate's experience by observing the number of different experiences reported, the roles performed, the companies in which they have been performed, and the number of months of experience. We therefore expect LIBFD1 to be a valid indicator of participants' leadership skills. Social capital is also key to the development of effective leadership (e.g., Balkundi & Kilduff, 2005; Hitt & Ireland, 2002). Levels of leadership skills can be observed through LinkedIn profiles by means of visible signals, such as the number and type of leadership activities performed and the recommendations and validations received from contacts (Roulin & Levashina, 2019). LIBFD2 (social capital) collects the number of user contacts and the validations and recommendations received. It is therefore possible to argue that LIBFD2 will be a valid signal of participant leadership skills. In line with the above, we propose the following hypothesis:

*H*1: LIBFD1 (*H*1a) and LIBFD2 (*H*1b) will significantly and positively correlate with leadership skills.

Signals of Planning

The planning skill is related to the capacity to formulate plans and perform mental simulations of the sequence of actions required to achieve a particular objective, which includes the ability to consider any restrictions that may exist in the development of such actions (Mumford et al., 2017). As Roulin and Bangerter (2013) point out, this ability can be observed on LinkedIn by observing the degree to which the user offers a complete and well-structured profile, and the breadth and variety of activities the user performs and manages at any time (e.g., development of volunteering activities while pursuing a university degree or working). Markers of this skill are found in LIBFD4, a dimension that refers to the degree to which a participant has completed their profile (number of profile categories completed and entries in the About section), the charitable causes in which the user is involved, and the interests noted.

It would seem that recruiters are able to infer this ability with some accuracy from information found on LinkedIn (Roulin & Levashina, 2019). It is therefore possible to argue that this dimension may be a valid signal of the planning ability of candidates. We therefore propose the following hypothesis:

*H*2: LIBFD4 will significantly and positively correlate with planning skills.

Signals of Communication

Communication skills can be observed on LinkedIn through the analysis of a candidate's description of their professional profile (Roulin & Levashina, 2019).

Various studies have also shown how communication skills are related to the development of a professional network (McEwan & Guerrero, 2010). Consequently, the number of user contacts and the validations and recommendations received may be a sign of the degree to which a candidate interacts with their network to increase their social capital. It is therefore possible to argue that a candidate's social capital expressed in LIBFD2 will be a valid signal of a candidate's communication skills. We therefore propose the following hypothesis.

*H*3: LIBFD2 will significantly and positively correlate with communication skills.

Signals of Teamwork

Teamwork skills are strongly influenced by a participant's ability to network (Matook et al., 2015). Individuals that are able to form relationships establish a higher number of connections and greater participation in groups, which allows them to connect relevant organizational environments (Valkenburg et al., 2006; Zide et al., 2014). In addition, both the validations and the recommendations referred to by others could indicate the sufficiency with which the candidate can perform the responsibilities of the job. As pointed out by O'Neill et al. (2019), one of the fundamental dimensions to explore professionals' teamwork capacity is precisely to analyze the degree to which they are able to adequately develop the behaviors related to the task. In fact, teamwork behaviors are related to task performance (e.g., Aguado et al., 2014). This ability to work in a team can be visible on LinkedIn through the group activities developed by the candidate, their membership in students' clubs, or team sports (Roulin & Levashina, 2019). The above LinkedIn profile characteristics are included in LKDBF2. It is therefore possible to argue that LIBFD2, a dimension that collects the relational activity of professionals, will be a valid signal of teamwork skills.

LIBFD4, breadth of non-professional information, refers to the degree to which a LinkedIn user publishes their non-professional interests of a pro-social nature. The relationship between cooperation and pro-social behaviour is extensively reported in the literature (e.g., Batson, 2011). Individuals who develop more supportive and cooperative behaviour tend to be involved in voluntary activities and are more likely to assist others (Gintis et al., 2003). In addition, many studies indicate that individuals with higher extraversion and agreeableness are more likely to offer information about themselves (Smith et al., 1996). These personality traits have stronger correlations with competencies related to support for and cooperation with others (Bartram, 2005). Based on the above, we can posit that LIBFD4 will be a valid signal of the ability to work in a team:

*H*4: LIBFD2 (*H*4a) and LIBFD4 (*H*4b) will significantly and positively correlate with teamwork skills.

Signals of Problem Solving

Problem-solving skills include the ability to assimilate new knowledge and behaviours aimed at keeping information constantly up to date. Many authors have highlighted how interest in individual learning is crucial to the acquisition and use of knowledge (Schraw et al., 2001). This interest in acquisition of new knowledge allows for the development of new competencies (Danneels, 2002) and facilitates the achievement and development of innovative outcomes (Zahra et al., 2000). We therefore expect LIBFD3 to be a valid signal of a participant's problem-solving skills.

Given that the acquisition and use of new knowledge involves a social process (Yli-Renko et al., 2001), an individual's connections take on additional importance (Kaish & Gilad, 1991). In today's interconnected world, many of the technical problems that arise in day-to-day work are solved by consulting specialized professional networks (Little, 2012). The dynamic ability of technical communities to resolve specific problems and search for solutions to novel problems is well documented (e.g., the R Project for Statistical Computing). Also, problem solving refers to the ability to analyze, identify, and evaluate alternatives in order to solve problems. This can be explored through the links and interactions with other users and with content presented by different groups, associations, etc. An individual's social capital plays an important role in accessing these resources. Individuals with greater relational capital will also have increased access to the support required to solve problems in their work activity. It is therefore possible to argue that LIBFD2 will be a valid signal of an individual's problem-solving abilities.

*H*5: LIBFD2 (*H*5a) and LIBFD3 (*H*5b) will significantly and positively correlate with problem solving skills.

Signals of Entrepreneurial and Commercial Thinking

Entrepreneurial and commercial thinking skills characterize individuals with the ability to track markets and competitors, identify business opportunities, and demonstrate awareness of financial matters and organizational phenomena. These skills characterize individuals who are able to seek out and identify business opportunities and take on activities to pursue the development of opportunities (Chell, 2013; Davis et al., 2020; Gabrielsson & Politis, 2012). Various studies indicate that a candidate's experience is related to the abilities required to generate this entrepreneurial vision and opportunity development (e.g., Plambeck, 2012). LIBFD1 captures the breadth of professional experience referred to by the candidate in their profile. It is therefore possible to argue that the extent of the professional experience collected in LIBFD1 can be a valid signal of entrepreneurial and commercial thinking skills.

In addition, a key characteristic of individuals with entrepreneurial capacities is their ability to establish connections and exploit their social capital to pursue their initiatives (e.g., Casson & Giusta, 2007). Social capital is clearly crucial in those candidates with strong commercial and entrepreneurial thinking and is used to achieve competitive advantages (e.g., Anderson & Miller, 2002). It is therefore possible to argue that LIBFD2 will be a valid signal of a candidate's entrepreneurial and commercial thinking skills. Based on the above, we propose the next hypothesis.

*H*6: LIBFD1 (*H*6a) and LIBFD2 (*H*6b) will significantly and positively correlate with commercial and entrepreneurial skills.

Signals of Information Seeking, Conflict Management and Adaptability

Roulin and Levashina (2019) found that HR professionals found it more difficult to infer skills related to information seeking, conflict management, and adaptability, since they are less visible skills in the LinkedIn profile (compared, for example, to leadership skills). In terms of the signalling theory, recruiters do not find valid signals to adequately infer these skills. However, the LIBFD do not capture aspects of the content of the signals in each candidate's professional profile (i.e., the content of university education, such as a degree in mathematics). Instead, the LIFBD capture formal aspects that are present in the professional profile (i.e., the number of words that the candidate devotes to presenting their professional experience). This approach to the analysis of LinkedIn profiles may therefore constitute a valid signal of these less visible skills. The extent of professional and academic experience, developed social capital, and involvement in non-professional activities results from a particular professional career that may have facilitated or limited the development of these skills. However, it is important to explore the extent to which these less visible skills are signalled in the LinkedIn Big Four. In the absence of empirical evidence that would allow us to hypothesize such relationships, we propose the following research question:

RQ1: To what extent can the dimensions contemplated in the LIBFD model be considered valid signals of less visible skills such as information seeking, conflict management, and adaptability?

Prediction of Soft Skills Based on LinkedIn Big Four Dimensions

As we hypothesized, users will signal certain skills through LinkedIn Big Four indicators. These signals are taken into account by recruiters, who then go on to make inferences about a candidate's soft skills. These inferences often develop from an integrated view of the various signals considered (Fernandez et al., 2021). It would therefore seem reasonable to analyse the degree to which the standardized and systematic use of the different LIBFD signals can provide an accurate estimation of a candidate's soft skills. This prediction problem in personnel selection is usually addressed by the development of multiple regression models (e.g., Edwards & Edwards, 2019). In addition to the use of such regression models, our study will also employ classification statistics (Fleiss, 1981). Following the strategy developed by Fernandez et al., (2021) in the prediction of personality through LinkedIn, the use of classification statistics will allow us to approach the study of the probability with which different levels of soft skills can be classified from LIBFD. We therefore propose the following research question.

RQ2: Is it possible to predict soft skills based on LIBFD signals? If so, how accurately? What differences exist in the accuracy with which different soft skills are predicted?

Method

Participants

This study used information gathered from 169 experienced professionals (82.8% men) in the ICT sector, working as software developers, analysts, and project managers, aged between 22 and 57 (mean = 34.57, *SD* = 8.81). All the participants belonged to a Spanish-based international company with over four thousand employees worldwide. The main activity of this company is focused on applications management and development in areas such as cybersecurity, Cloud services, and solutions based on Enterprises Resources Planning Software.

Measures

LinkedIn Profile

Four scores were obtained from the LinkedIn profiles of the participants, according to the four underlying dimensions proposed by Aguado et al. (2019): 1) breadth of professional experience, 2) social capital, 3) interest in updating knowledge, and 4) breadth of non-professional information. For the measurement of the four dimensions, we employed the easy-to-use and understandable rubrics proposed by Andrés et al. (2022). The rubrics used were developed following the standards proposed by Wenzlaff et al. (1999). These standards include: (a) identification of the observable aspects to be assessed, (b) preparation of the response scale that will be used to assess the aspects included in the rubric, and (c) narrative and precise description of the characteristics associated with each category of the response scale. The analysis of the quality of the rubrics showed adequate inter-rater validity (an average kappa index .85) and adequate temporal reliability (an average of test-retest correlation 1.00). The use of standardized evaluations of content is an important element for improving the validity of decisions based on information in the field of SNW (Roth et al., 2016).

Self-reported Soft Skills

Soft skills were measured by means of a self-reported questionnaire. We asked the participants about the degree to which they regularly demonstrated the 9 skills chosen for our study. Every skill was assessed by means of five adapted items from Woo et al. (2008) and Bartram (2005). The questionnaire was comprised of forty-five Likert four-point items (5 items for every skill) as follows: 1) "I'm not good enough"; 2) "I'm fairly good"; 3) "I'm very good"; 4) "I'm an expert". Acceptable Cronbach's alpha reliability coefficients were achieved: Leadership (α = .80; sample item: "Leading and coordinating people who work with me"); Teamwork (α = .77; sample item: "Understanding the concerns and points of view of the people I work with, even when they are different from my own"); Planning (α = .86; sample item: "Establishing in advance the actions and resources needed to achieve the proposed goals"; Conflict Management (α = .80; sample item: "In the face of conflict, proposing collaborative actions to solve the discrepancies that arise among the members of my network"); Communication (α = .81; sample item: "Preparing and clearly and precisely explaining the advantages of my points of view"); Problem solving (α = .85; sample item: "Looking for opportunities to come up with innovative ideas and new ways of working"); Information Seeking (α = .87: sample item: "Actively seeking learning opportunities that will allow me to develop as an expert in my field of work"); Adaptability (α = .83; sample item: "Modifying the way I act in new or unclear situations to adapt to new circumstances"); and Entrepreneurial and Commercial Thinking (α = .82; sample item: "Being aware of the labour market to be able to detect new job opportunities").

Procedure and Data Analysis

The assessment of the LinkedIn profiles was carried out by a group of 12 human resources professionals. The soft skills measures were obtained through an unproctored online questionnaire completed by the participants. They were informed of the aims of the research and their informed consent was required.

In order to validate our hypotheses and our first research question, we carried out a correlational analysis. We developed two strategies to answer our second research question and explore the extent to which soft skills could be predicted from LIBFD scores. As an initial strategy, we ran various hierarchical stepwise regression models using soft skills as dependent variables and LIBFD measures as independent variables. Firstly, gender and age control variables were included for all models. Secondly, the LIBFD were entered. Table 4 shows the results obtained.

The second strategy, based on Fernandez et al. (2021), was to explore the accuracy of participant classification based on their LIBFD scores. Every soft skill was categorized into two levels: absent skill (scores below 66%) versus present skill (scores above 66%). Every soft skill was considered as a dependent variable, while the LIBFD were considered as independent variables. We used discriminant analysis as a classification technique. We used various indicators to study the quality of the classifications made: sensitivity, specificity, hit rates, and likelihood ratio +. Sensitivity indicates the percentage of participants correctly classified in the condition "presence of the soft skill". Specificity indicates the percentage of cases that are correctly classified in the condition "absence of the soft skill". Hit rates indicates the total percentage of cases correctly classified in every condition. Positive likelihood ratio (LR+) is the number of positives (presence of the skill) correctly classified, divided by the number of misclassified positives (presence of the skill), and thus indicates the ratio of correctly and incorrectly classified positives (e.g., García-Izquierdo & García-Izquierdo, 2006). The classification results used for the construction of the indicators were those obtained from the leave-one-out cross validation procedure. The random value was 50%, so scores higher than this value were considered remarkable.

Results

Table 3 shows the descriptive statistics and inter-correlations of the variables. The statistical power analysis of the correlations obtained was carried out with G*Power (Faul et al., 2007). The cut-off point for

Table 3. Descriptive Statistics and Correlations

		Mean	*SD*	Alpha	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Gender	1.11	7.40	1.00	.135	.035	.041	.155*	.166*	.126	.042	.175*	.090	.153*	.121	.064	.016	.089
2	Age	34.57	8.81	1.00		.292**	.149	-.042	-.025	.034	-.019	.051	.039	.004	-.033	-.077	.040	-.010
3	LIBFD1	0.09	4.34	.89			.569**	.206**	.286**	.215**	.165*	.155*	.113	.297**	.200**	.219**	.167*	.116
4	LIBFD2	0.06	3.73	.72				.330**	.451**	.324**	.212**	.199**	.129	.399**	.245**	.339**	.127	.178*
5	LIBFD3	-0.01	2.04	.40					.383**	-.028	.048	-.010	-.015	.141	.092	.050	.094	-.058
6	LIBFD4	0.08	2.76	.70						.155*	.108	.066	.016	.198**	.072	.233**	.128	.109
7	Leadership	24.28	4.57	.80							.600**	.695**	.734**	.631**	.634**	.587**	.564**	.671**
8	Teamwork	27.27	3.89	.77								.511**	.701**	.562**	.616**	.481**	.568**	.658**
9	Planning & Organizing	23.93	4.62	.86									.669**	.671**	.568**	.603**	.607**	.647**
10	Conflict Management	25.11	4.13	.80										.624**	.762**	.607**	.674**	.750**
11	Entrepr. & Com. Thinking	22.44	4.92	.82											.683**	.659**	.530**	.577**
12	Communication	23.38	4.79	.81												.608**	.605**	.537**
13	Problem Solving	22.75	4.86	.85													.694**	.537**
14	Information Seeking	27.02	4.21	.87														.564**
15	Adaptability	26.90	4.01	.30														

*p < .05, **p < .01.

Table 4. Regression Model Results

	R^2	β	*F*	*p*-value	VIF
Leadership					
Model 1: Control Variables	.016		1.355	.261	
Gender		.123		.114	
Age		.017		.828	
Model 2: With LinkedIn Variables	.121		5.622	< .0001	
Gender		.117		.115	1.02
Age		-.042		.585	1.11
LIBFD1		.055		.548	1.58
LIBFD2		.294**		.001	1.48
ΔR^2 Model 2 vs. Model 1				<. 0001	
Teamwork					
Model 1: Control Variables	.002		0.195	.823	
Gender		.045		.564	
Age		-.025		.753	
Model 2: With LinkedIn Variables	.054		2.347	.057	
Gender		.042		.585	1.02
Age		-.076		.347	1.11
LIBFD1		.089		.354	1.58
LIBFD2		.171		.066	1.48
ΔR^2 Model 2 vs. Model 1				.013	
Enterpreneurial and Commercial Thinking					
Model 1: Control Variables	.024		2.018	.136	
Gender		.155*		.046	
Age		-.017		.822	
Model 2: With LinkedIn Variables	.195		7.901	< .0001	
Gender		.153*		.036	1.05
Age		-.108		.150	1.14
LIBFD1		.136		.127	1.59
LIBFD2		.341**		< .0001	1.71
LIBFD4		-.023		.778	1.32
ΔR^2 Model 2 vs. Model 1				< .0001	
Planning & Organizing					
Model 1: Control Variables	.031		2.018	.071	
Gender		.171*		.028	
Age		.027		.724	
Model 2: With LinkedIn Variables	.070		3.089	.017	
Gender		.168		.028	1.02
Age		-.014		.856	1.11
LIBFD1		.064		.503	1.58

Table 4. Regression Model Results (continued).

	R^2	β	F	p-value	VIF
LIBFD2		.158		.086	1.48
ΔR^2 Model 2 vs. Model 1				.035	
Communication					
Model 1: Control Variables	.017		1.438	.240	
Gender		.127		.103	
Age		-.500		.519	
Model 2: With LinkedIn Variables	.089		4.005	.004	
Gender		.124		.101	1.02
Age		-.113		.151	1.11
LIBFD1		.123		.192	1.58
LIBFD2		.187*		.041	1.48
ΔR^2 Model 2 vs. Model 1				.002	
Problem Solving					
Model 1: Control Variables	.012		0.971	.381	
Gender		.076		.333	
Age		-.087		.264	
Model 2: With LinkedIn Variables	.145		5.515	< .0001	
Gender		.058		.438	1.05
Age		-.149		.056	1.14
LIBFD1		.081		.379	1.59
LIBFD2		.281**		.003	1.71
LIBFD4		.070		.399	1.32
ΔR^2 Model 2 vs. Model 1				< .0001	
Information Seeking					
Model 1: Control Variables	.002		0.143	.867	
Gender		.011		.890	
Age		.039		.622	
Model 2: With LinkedIn Variables	.028		1.598	.192	
Gender		.151		.880	1.02
Age		-.139		.890	1.11
LIBFD1		.170*		.035	1.09
ΔR^2 Model 2 vs. Model 1				.035	
Adaptability					
Model 1: Control Variables	.008		0.703	.497	
Gender		.092		.241	
Age		-.023		.771	
Model 2: With LinkedIn Variables	.041		2.332	.076	
Gender		.088		.255	1.02
Age		-.049		.527	1.04
LIBFD2		.182*		.020	1.02
ΔR^2 Model 2 vs. Model 1				.020	

an adequate effect size (p =. 50) (Cohen, 1988) with a statistical power (1 - β = .90) and a sample size (n = 169) was established at r = .20, so we focused on correlations equal to or above .20. As can be seen in Table 3, we found positive and significant intercorrelations between the LinkedIn dimensions. The highest correlation was between LIBFD1 and LIBFD2 (r = .57, p < .001). The average of these correlations is .37.

Similarly, the correlations between the estimated soft skill scores are all positive and significant, with an average of .62. In accordance with our hypothesis, we found positive and significant correlations between leadership and LIBFD1 (r = .21, p < .001) and LIBFD2 (r = .30, p < .001). This indicates that the breadth of a candidate's professional experience (LIBFD1) and their social capital (LIBFD2) are valid signals of a candidate's leadership skills, which allows us to confirm our *H*1. Regarding *H*2, correlations with lanning and organization are positive, significant, and with an effect size greater than .20 with LIBFD2 (r = .20, p < .001), but not with LIBFD4 as we proposed. This indicates that non-professional information included in the profile is not a valid signal of an individual's ability to plan and organize, which lead us to reject our second hypothesis (*H*2). With regard to communication skills, we observed positive and significant correlations with LIBFD2 (r = .24, p < .001), which supports our third hypothesis (*H*3), and also with LIBFD1 (r = .20, p < .001). These results indicate that, once again, both the breadth of a candidate's professional experience and their social capital are valid signals of communication. Regarding teamwork, we found positive and significant correlations with LIBFD2 (r = .21, p < .001) but not for LIBFD4 as we hypothesized. A candidate's social capital therefore constitutes a valid signal of their team-working skills. However, the extent of non-professional activities reported in the profile does not constitute a valid signal. These results only allow us to partially accept our fourth hypothesis (*H*4).

Table 5. Results Classification

	Sensibility in Percentage	Specificity in Percentage	HitRates in Percentage	Positive Likelihood Ratio
Leadership	61.8	59.6	61.0	2.39
Com & Enterpr. Thinking	63.6	65.6	64.6	2.00
Problem Solving	57.0	54.1	55.7	1.60
Planning & Organizing	58.6	60.6	59.6	1.57
Communication	61.0	65.6	63.4	1.63

Problem-solving skill correlates positively and significantly with LIBFD2 (r = .34, p < .001), but not with LIBFD3 as we hypothesized. There is therefore only partial evidence to support our fifth hypothesis (*H*5a). We also found positive and significant correlations with LIBFD4 (r = .23, p < .001) and with LIBFD1(r = .22, p < .001). To summarise, breadth of professional experience, social capital, and breadth of non-professional activity reported by candidates are valid signals of their problem-solving skills.

Finally, in relation to entrepreneurial and commercial thinking, our results show positive and significant correlations with LIBFD1 (r = .30, p < .001) and with LIBFD2 (r = .40, p < .001), which allows us to support our hypothesis *H*6 (a and b). Correlations were also found with LIBFD4 (r = .20, p < .001). We can therefore conclude that breadth of a candidate's professional experience, social capital, and breadth of non-professional activities developed are valid signals of entrepreneurial and commercial thinking.

Moving on to answer our first research question, we observed that LIBFD do not correlate significantly and do not have values higher than .20 with conflict management, information seeking, and adaptability, which indicates that LIBFD do not constitute valid signals of those soft skills.

As shown in Table 4, the LIBFD provide additional explanation for the variance explained by gender and age control variables for the following soft skills: leadership, entrepreneurial and commercial thinking, communication, and problem solving. It is LIBFD2 that produced this increase, for which significant regression coefficients were obtained: leadership (LIBFD2 β = .294, p < .001), entrepreneurial and commercial thinking (LIBFD2 β = .341, p < .001), communication (LIBFD2 β = .187, p < .05), and problem solving (LIBFD2 β = .281, p < .001).

Table 5 shows the classification results obtained. This classification was only carried out with those LIBFD soft skills that showed a significant increase in explained variance: leadership, entrepreneurial and commercial thinking, planning and organization, communication, and problem solving.

All the discriminant analysis models present a significant Wilks' lambda, except for communication (Wilks' lambda = .983, p = .131). We found significant results for: leadership (Wilks' lambda = .951; p = .007), entrepreneurial and commercial thinking (Wilks' lambda = .887, p < .0001), planning and organization (Wilks' lambda = .970; p = .040), and problem solving (Wilks' lambda = .912, p = .001). As can be seen, overall ranking percentages (hit rate) between 55.7% (planning and organization) and 64.4% (entrepreneurial and commercial thinking) are obtained for the four soft skills considered. This classification percentage is balanced, as the values obtained for sensitivity and specificity are similar.

Discussion

This paper presents initial evidence of the relationships between individual soft skills and LinkedIn profiles. Our results indicate that the way in which individuals develop their career and the way they report it on LinkedIn are valid signals of the extent to which they have developed their soft skills. This is of great importance, as it allows recruitment and selection professionals to identify which signals from LinkedIn profiles prove useful for improving inferences about candidates' soft skills.

In line with our hypotheses, our results indicate that LIBFD are valid signals of leadership, communication, and entrepreneurial and commercial thinking. Although not in line with our hypotheses, LFBD are also shown to be valid signals of planning and organization, teamwork, and problem solving. However, there is no evidence that conflict management, information seeking, and adaptability can be inferred from these signals.

A closer look at the results allows us to appreciate the soft skills that are best signalled by the LIBFD. From largest to smallest: entrepreneurial and commercial thinking, leadership, communication, and problem solving.

It is also important to analyse the results in terms of which LIBFD are relevant signals. Our results seem to indicate that both the extent of professional experience developed (LIBFD1) and the social capital developed by the professional (LIBFD2) are the best signals for inferring soft skills. The extent of non-professional activity developed by professionals and reported on LinkedIn (LIBFD4) is only relevant for two skills (entrepreneurial and commercial thinking, and problem solving). Finally, interest in keeping knowledge up to date (LIBFD3) is not a valid signal for any of the soft skills studied. In short, our results indicate that candidates whose LinkedIn profiles display a greater extension of their professional career (LIBFD1) and social capital (LIBFD2) tend to have more developed skills in entrepreneurial and commercial thinking, leading, communicating, and problem solving. The classification matrix backs up these results. Using LIBFD, an individual's high vs. low in these skills are correctly classified in 64.6% of cases (entrepreneurial and commercial thinking), 63.4% (problem solving), 61% (leadership), and 59.6% (communication).

These results are consistent with and complementary to those of Roulin and Levashina (2019). In their study, visible soft skills (e.g., leadership, planning, communication and teamwork) are better inferred by recruiters than non-visible soft skills (e.g., information seeking, problem solving, conflict management, and adaptability). Our research yields similar results and shows that more visible skills generate valid signals on LinkedIn, which is not the case for non-visible signals. Therefore, LinkedIn may be a valid vehicle for inferring some but not all soft skills. No valid signals were found for information seeking, conflict management, and adaptability.

Our study also reveals some interesting differences with respect to Roulin and Levashina's (2019) findings. We found valid signals for problem solving. A candidate's social capital is a valid signal of this skill. As we hypothesised, a candidate's network allows increased access to various ways of solving problems that may arise. In contrast to Roulin and Levashina (2019), we also introduced an additional soft skill (entrepreneurial and commercial thinking), which is particularly well signalled on LinkedIn. These findings are in line with various studies that show how professional experience is related to greater development of business thinking, entrepreneurship, and greater success in the development of competencies related to business management (Dragoni et al., 2011; Gabrielsson & Politis, 2012). Our findings are also consistent with the idea that interacting with others and developing networks, both within and outside the organization, allows for quicker and easier access to information and increased job opportunities via a greater number of contacts and an enhanced reputation (Davis et al., 2020).

Finally, our research contributes to the study of LinkedIn as a selection method. The findings presented in this study provide evidence of the validity of LinkedIn for inferring soft skills. As Roth et al. (2016) point out, the LinkedIn-based applicant assessments made by hiring managers should converge (i.e., correlate) with test scores or self-reporting of the same qualifications. Given the use of SNW as a selection tool is widespread (Kluemper et al., 2016), and calls for research on improving the psychometric properties of selection methods (e.g., Levashina et al., 2014), our results provide value from two different perspectives. First, our study determines which candidate soft skills are being signalled in the LinkedIn profile and which are not. This opens the door to a systematic study of which specific signals recruiters can use for decision making.

Second, our results provide evidence about the way in which LIBFD may prove useful in helping to understand the behaviour of individuals when developing their LinkedIn profile and showcasing their strengths to their network.

Limitations

This study is not without limitations, since it solely focused on the specific sector of ICT. Although this sector is experiencing significant market growth, this sole focus limits the generalization of results for other sectors. In addition, while the LIBFD model demonstrates the way in which candidates develop their professional profiles, it says nothing about their specific content.

It would therefore seem necessary to broaden the scope of these results along three lines. First, the study of profiles and candidates in other sectors and productive areas. Second, an analysis of the specific content of LinkedIn profiles using natural language processing and other artificial intelligence and human resources analytics tools and algorithms (e.g. Álvarez et al, 2022; Edwards & Edwards, 2019). Third, an examination of social capital connections using organizational network analysis; for example, exploring the degree to which users interact with content developed by other users.

An additional issue is the use of LIBFD as a signal. LIBFD do not collect information regarding the specific content of profiles but collect quantitative information regarding a professional's use of LinkedIn to showcase their strengths. The information collected in LIBFD (e.g., number of companies the professional has worked in) is different from the specific content (e.g., that the professional has worked in a certain company). Therefore, LIBFD are valid and complementary signals to those used by recruiters when examining the content of the profile. Future research should explore the extent to which this complementarity increases the quality of the inferences that recruiters make.

Finally, the decision to use self-ratings to assess skills is not exempt from criticism. Several studies show that self-reporting can provide higher estimates than assessments made by others. However, we decided to use this strategy for three reasons. First, bias in self-assessments seems to be greater in evaluative contexts than in research contexts (Fleenor et al., 2010). Second, studies seem to indicate that leniency in self-rating assessment is rather low (Heidemeier & Moser, 2009). Third, there is ample evidence that people are able to provide accurate estimates of their own skills (e.g., Ackerman & Wolman, 2007). In short, we argue that the self-reported estimates of participant soft skills used in this study will not be biased by overestimation or leniency.

Implications for Practice

The findings presented in this study have implications for professional practice. A candidate's LinkedIn profile can be analysed using the LIBFD model, which can be connected with the soft skills they may have developed. In this way, professionals can avoid unsystematic analysis of information when making decisions based on the information contained in LinkedIn profiles (Aguado et al., 2019). This makes a clear contribution for both jobseekers and practitioners when making decisions in a personnel selection context.

Conflict of Interest

The authors of this article declare no conflict of interest.

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