The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/0143-7720.htm

The emotional and social side of analytics professionals: an exploratory study of the behavioral profile of data scientists and data analysts

Received 21 July 2020
Revised 20 December 2020
5 May 2021
10 July 2021
23 September 2021
7 December 2021
Accepted 11 December 2021

Sara Bonesso and Fabrizio Gerli
Department of Management, Ca' Foscari University of Venice, Venice, Italy, and
Elena Bruni
Department of Management, WU Vienna – Institute for Organization Studies, Wien, Austria

Abstract

Purpose – Analytics technologies are profoundly changing the way in which organizations generate economic and social value from data. Consequently, the professional roles of data scientists and data analysts are in high demand in the labor market. Although the technical competencies expected for these roles are well known, their behavioral competencies have not been thoroughly investigated. Drawing on the competency-based theoretical framework, this study aims to address this gap, providing evidence of the emotional, social and cognitive competencies that data scientists and data analysts most frequently demonstrate when they effectively perform their jobs, and identifying those competencies that distinguish them.

Design/methodology/approach – This study is exploratory in nature and adopts the competency-based methodology through the analysis of in-depth behavioral event interviews collected from a sample of 24 Italian data scientists and data analysts.

Findings – The findings empirically enrich the extant literature on the intangible dimensions of human capital that are relevant in analytics roles. Specifically, the results show that, in comparison to data analysts, data scientists more frequently use certain competencies related to self-awareness, teamwork, networking, flexibility, system thinking and lateral thinking.

Research limitations/implications – The study was conducted in a small sample and in a specific geographical area, and this may reduce the analytic generalizability of the findings.

Practical implications – The skills shortages that characterize these roles need to be addressed in a way that also considers the intangible dimensions of human capital. Educational institutions can design better curricula for entry-level data scientists and analysts who encompass the development of behavioral competencies. Organizations can effectively orient the recruitment and the training processes toward the most relevant competencies for those analytics roles.

Originality/value – This exploratory study advances our understanding of the competencies required by professionals who mostly contribute to the performance of data science teams. This article proposes a competency framework that can be adopted to assess a broader portfolio of the behaviors of big data professionals.

Keywords Behavioral competencies, Behavioral event interview, Big data, Competency-based approach, Data analytics jobs, Data analysts, Data scientists, Emotional intelligence, Soft skills

Paper type Research paper

This research has been conducted at the Ca' Foscari Competency Centre of the Ca' Foscari University of Venice. The authors thank all the colleagues of the Ca' Foscari Competency Centre with whom the authors had the opportunity to share their research. The authors express their gratitude to the reviewers and the editor, whose support was fundamental to direct the manuscript.

International Journal of Manpower
Vol. 43 No. 9, 2022
pp. 19-41
Emerald Publishing Limited
0143-7720
DOI 10.1108/IJM-07-2020-0342

1. Introduction

Organizations are progressively embracing a data-driven culture that puts big data technologies and their related analytic methods at the center of their work (Ciarli *et al.*, 2020; Davenport and Harris, 2017; Gandomi and Haider, 2015; Lorenz *et al.*, 2015; Singh *et al.*, 2021; Škrinjarić and Domadenik, 2020; Vidgen *et al.*, 2017). While investments in big data technologies are becoming of paramount importance, it is at least as important to build a team of data science professionals who can use these technologies effectively and who possess the set of competencies needed to acquire, organize, process and present data effectively (Davenport and Patil, 2012). In the past few years, the demand for knowledgeable people to fill data analytics roles, particularly data scientists and data analysts, has shown a dramatic growth and – at the same time – a great shortage of such individuals (LinkedIn, 2020; World Economic Forum, 2020).

The misalignment between the demand for and the availability of data scientists and data analysts in the labor market needs to be addressed at the educational level, on the one hand, with dedicated programs aiming at developing the required competencies, and at the organizational level, on the other hand, by orienting the recruitment process toward the most relevant competencies for those holding these roles in the working context. Even though, in recent years, a great deal of effort has been devoted, by both practitioners and the academic community, to define the technical skills that differentiate data analysts from data scientists (Costa and Santos, 2017; Davenport, 2014; De Mauro *et al.*, 2019; Harris and Mehrotra, 2014; Verma *et al.*, 2019), their behavioral competencies have not been thoroughly investigated, with relevant implications in terms of the design of curricula and of skills development. Indeed, despite the increasing educational offerings in this field (e.g. through a plethora of courses offered by established MOOC (massive open online course) platforms) [1], these programs show a misalignment between their learning objectives and the industry needs in terms of behavioral competencies (Bowers *et al.*, 2018). In essence, limited attention has been given to the identification of the soft skills required by these knowledge-intensive roles. Unlike technical skills, the measurement and the development of behavioral competencies present more challenges for the educational institutions, since they require the implementation of dedicated assessment tools and experiential learning methodologies (Kolb, 2015; Hoover *et al.*, 2010).

Undoubtedly, technical skills, which represent the so-called tangible or technical elements of human capital (McGuirk *et al.*, 2015), constitute the threshold competencies for entry into the data analytics labor market (Dubey and Tiwari, 2020). However, as the complexity of the tasks and projects in which analysts and scientists are involved increases, the intangible elements – or behavioral competencies – are assuming increasing relevance for these roles. Behavioral competencies play a vital role in supporting these workers in understanding the business environment, finding creative solutions, promoting collaboration among their team members and also becoming aware of internal and external stakeholders' needs (Costa and Santos, 2017; De Mauro *et al.*, 2019; Mitchell *et al.*, 2021; Shirani, 2016; Verma *et al.*, 2019). Indeed, research (Beck and Libert, 2017; Capgemini, 2019; Ozkan-Ozen and Kazancoglu, 2021; Singh *et al.*, 2021) has claimed that behavioral/emotional intelligence competencies are expected to grow in importance over the next few years and become a differentiator in the digital era in which artificial intelligence and machine learning will progressively automate routine tasks. However, in the past decade, the literature has highlighted the relevance of behavioral competencies for enabling data analysts and scientists to achieve an outstanding performance, and these studies are primarily based on anecdotal evidence or analyses of Web-based job postings and LinkedIn profiles (De Mauro *et al.*, 2019; Ecleo and Galido, 2017; Verma *et al.*, 2019).

Against this backdrop, this study addresses the following research questions: What are the behavioral competencies that data scientists and data analysts most frequently demonstrate when they effectively perform their jobs? What are the behavioral competencies that distinguish these two roles?

This research, drawing on the competency-based literature and adopting the behavioral event interview technique (Boyatzis, 2008, 2009; Boyatzis and Goleman, 2007; Spencer and Spencer, 1993) on a sample of data analysts and data scientists operating in the Italian context, aims to advance the understanding of the intangible dimensions of human capital of these roles.

The article is structured as follows. The next section reviews the literature on the competency profile of data analysts and data scientists. Drawing on the human capital theory and the competency-based framework, this section points out the relevance for these roles of the intangible components of human capital and calls for a more in-depth investigation of the behavioral competencies that characterize them. Subsequently, the research design and competency-based methods are described. The exploratory findings delineating the behavioral competencies of the two roles are presented, with a specific focus on the skills that differentiate data scientists from data analysts. The article concludes by discussing the advances provided by this research and suggesting implications for educational institutions and human resource practitioners.

2. Theoretical background

2.1 Data scientists and data analysts: competency profiles of two fast-growing jobs

The last version of the *Future of Jobs Survey* of the World Economic Forum (2020) confirms a relevant trend that practitioners and academics have started to reveal in recent years: demand across industries for data scientists and data analysts experienced the highest growth. As a result of this fast-growing demand, there is a significant shortage of these professionals in the labor market, and they are among the most difficult workers to recruit (LinkedIn, 2019, 2020). To support the educational system in satisfying the labor market demand and to provide guidance to human resources management departments in their recruitment processes, experts and scholars in the field of data analytics have helped to define the competences of each of the two roles. As summarized in Table 1, the main differences can be ascribed to the type of data these individuals work with, the main tasks they are asked to perform and the knowledge and tools they deploy (Costa and Santos, 2017; De Mauro *et al.*, 2019; Harris and Mehrotra, 2014; Verma *et al.*, 2019).

Job characteristics	Data analyst	Data scientist
Type of data	Structured and semi-structured, mostly numeric data	Structured and unstructured data, numeric and nonnumeric data (such as images, sound, text), big data
Main tasks	Report, predict, prescribe and optimize	Explore; discover; investigate; visualize; communicate and disseminate findings and practices; design, build, deploy and optimize data artifacts; identify patterns and trends in data; assure efficient data flows and data-related tasks; make sure all his/her skills are independent of data volume and structure; help business management and performance through his/her analytical and decision-making capabilities
Knowledge and tools	Statistical and modeling knowledge and tools usually contained in a data repository	Scientific method; computing theories, methods and tools, computer systems design; manipulate data (e.g. SQL); stages of data flow; data characteristics and challenges; security, privacy and ethics: mathematical languages (such as R and Python); machine learning; natural language processing and open-source tools that access and manipulate data on multiple servers (such as Hadoop)

Source(s): Costa and Santos, 2017; De Mauro *et al.*, 2019; Harris and Mehrotra, 2014; Verma *et al.*, 2019

Table 1. Job characteristics that distinguish data scientist from data analyst

According to Granville (2014), data analysts conduct database modeling at a high level, defining metrics and dashboards, retrieving and producing executive reports, and designing alarm systems. Thus, they are able to describe trends and translate their results into business terms. In comparison to analysts, data scientists are more technically oriented, since they rely strongly on sophisticated statistical and programming skills (Verma *et al.*, 2019). This technical profile has been confirmed by some surveys (Ecleo and Galido, 2017; LinkedIn, 2019), which state that data mining, data analysis and the use of Python, R, and machine learning SQL, SPSS, SAS and statistical modeling are the most commonly requested skills of data scientists. Davenport (2014) defines a data scientist as a hybrid figure who combines the following traits: *hacker*, capable of coding and using big data technology architectures; *scientist*, designing experiments and generating and testing hypotheses; *trusted adviser*, supporting executives in the decision-making process; *quantitative analyst*, conducting advanced statistical analysis of structured and unstructured data and mastering the machine learning approach; and *business expert*, using their knowledge about the specific business to enable them to interpret the results of their analysis and provide valuable solutions.

As demonstrated by a recent longitudinal study of job skills for entry-level data analytics roles based on the analysis of job postings (Dong and Triche, 2020), the fast pace of technological changes requires these professionals to constantly keep up with the field, continually updating their competencies and knowledge. The authors identified the general technical skills (analytics, statistics, modeling, model development and data management) and software package skills, which trended over time, and contribute to the human capital of these roles, namely, those knowledge, skills and other personal characteristics (Becker, 1993; Wright and McMahan, 2011), which represent a strategic asset for the company (Barney, 1991; Sweetland, 1996). By shifting the attention from a static and collective view of human capital to an individual and process perspective, studies maintain that people contribute to firm's performance only when they consciously translate their knowledge and skills into decisions and concrete actions in their workplace (Unger *et al.*, 2011; Wright and McMahan, 2011).

In this regard, people's effectiveness in the organizational environment is not purely based on their tangible or technical component of human capital, which is considered to be a threshold attribute (Goleman, 1998), namely, what is required for a minimum efficacy level in a certain position, especially in a knowledge-intensive job (Dubey and Tiwari, 2020). Instead, the intangible component, which encompasses personal, interpersonal and cognitive attitudes and behaviors (Boyatzis, 2009), assumes a salient relevance in distinguishing high-performing individuals. In this regard, human capital represents an important asset for firms to attain a sustainable competitive advantage only if it is unique and difficult to imitate (Vidotto *et al.*, 2017) and "intangible resources are more likely than tangible resources to produce a competitive advantage" (Hitt *et al.*, 2001, p. 14). However, the human capital theory has largely analyzed the technical competencies acquired through formal education and job training by means of scales and quantitative studies but has scantly addressed the behavioral dimension of human capital actually manifested in the work environment.

Therefore, to shed light on the behavioral dimensions of the human capital of new emerging job profiles such as data analysts and scientists, this study relies on the competency-based literature and its methodology that, for decades, has contributed to advance our understanding of the behavioral competencies that determine a substantial and important amount of the variance in predicting performance across different jobs.

2.2 The competency-based framework applied to data analysts and data scientists

A restricted group of studies has attempted to detect the behavioral competencies of data analysts and scientists, with a greater interest being shown in the latter role (Costa and Santos, 2017; Davenport and Patil, 2012; De Mauro *et al.*, 2019; Kim and Lee, 2016; Shirani, 2016; Verma *et al.*, 2019; Vidgen *et al.*, 2017). Table 2 reports the behavioral competencies most frequently

Data analyst	Data scientist
Communication (Lee and Han, 2008; Verma *et al.*, 2019) Interpersonal skills (Lee and Han, 2008) Teamwork (Verma *et al.*, 2019)	Adaptability (Kim and Lee, 2016) Business acumen (Costa and Santos, 2017; Davenport and Patil, 2012) Creative thinking (Davenport and Patil, 2012; Kim and Lee, 2016) Critical thinking (Shirani, 2016) Communication (Costa and Santos, 2017; Davenport and Patil, 2012; Kim and Lee, 2016; Shirani, 2016; Verma *et al.*, 2019) Customer orientation (Kim and Lee, 2016) Curiosity (Costa and Santos, 2017; Davenport and Patil, 2012; Vidgen *et al.*, 2017) Entrepreneurial attitude (Costa and Santos, 2017; Harris and Mehrotra, 2014) Exploring new ideas (Harris and Mehrotra, 2014) Leadership (Kim and Lee, 2016; Verma *et al.*, 2019) Problem-solving (Kim and Lee, 2016; Shirani, 2016) Self-motivation (Kim and Lee, 2016) Strategic thinking (Kim and Lee, 2016) Teamwork (Shirani, 2016; Verma *et al.*, 2019) Understanding business context (De Mauro *et al.*, 2019) Working independently (Vidgen *et al.*, 2017)

Table 2.
Soft skills of data scientists and data analysts identified by industry experts and analysis of job advertisements

associated with these two jobs. Among the few studies on data analysts, Lee and Han (2008) conducted an analysis of job advertisements from Fortune 500 corporate websites highlighting the relevance of communication and interpersonal skills. Communication is often emphasized as an important skill for data scientists (De Mauro *et al.*, 2019; Verma *et al.*, 2019), since these jobs require explaining results to non-expert audiences and playing an intermediary role between organizations and clients. Research conducted by Costa and Santos (2017) proposed a conceptual model that identifies, among the behavioral competencies of data scientists, business acumen, communication, entrepreneurial mindset, curiosity and interdisciplinary orientation. Davenport and Patil (2012) claimed that data scientists rely mainly on associative thinking to bring together different worlds and to find a pattern in diverse formats of data. Unlike analysts, data scientists exhibit an inquisitive and creative nature when interrogating data.

Despite the relevance of these studies, the state of the art of the behavioral competency profile of data scientists and analysts reveals an incomplete picture. First, the competency profile of these roles is still poorly defined, with a focus on some social and cognitive competencies only. Second, the few studies that aim to provide evidence about the competency profile of these roles mainly rely on the opinions of practitioners, adopting Delphi methodology (e.g. Vidgen *et al.*, 2017), or implementing text mining analysis of job advertisements and LinkedIn profiles (De Mauro *et al.*, 2019; Ecleo and Galido, 2017; Verma *et al.*, 2019). These pieces of research present a common limitation, namely, that they are primarily based on the perceptions of their participants and self-assessment techniques, which are subject to possible biases, since personal factors, like self-esteem and self-awareness, may affect how individuals use information about themselves, creating potential distortions in self-evaluations (Boyatzis *et al.*, 2002; Yammarino and Atwater, 1993).

To moderate these limitations and provide a representation of the behavioral competencies actually used by data analysts and data scientists in their work context, this study adopts the theoretical framework of behavioral competencies, which originated from the seminal work of David McClelland (1973) and is often mentioned in one of the major streams of research on emotional intelligence (Ashkanasy and Daus, 2005; Cherniss, 2010; McEnrue and Groves, 2006). Specifically, this research relies on the so-called "stream 4," which considers the behavioral level in measuring emotional intelligence (Boyatzis, 2018).

A behavioral competency is defined as a set of "related but different" behaviors "organized around an underlying construct called intent" (Boyatzis, 2009, p. 750) that "lead to or cause effective or superior performance" (Boyatzis, 1982, p. 23). Therefore, the concept of competency encompasses both actions (i.e. a set of alternative behaviors varying according to the situation) and the intent that moves an individual to express those behaviors (Boyatzis, 2009). As underlined in competency-based research conducted in different managerial professions and across different sectors (Bonesso *et al.*, 2020; Boyatzis, 1982; Camuffo *et al.*, 2012; Gutierrez *et al.*, 2012; Hopkins *et al.*, 2015), some competencies may be more relevant than others, depending on the specific characteristics of the job.

The framework of behavioral competencies is based on the theory of personality (McClelland, 1951) and on the contingency theory of action and performance (Boyatzis, 1982). According to the latter, optimum performance occurs when the individual's human capital is consistent with or fits the demands of the job and of the organizational environment (Boyatzis, 1982). On the other hand, the personality theory postulates the relationships among an individual's unconscious motives, self-schema and observed behavioral patterns (McClelland, 1951).

One of the fundamental principles of the competency-based approach is that what people think or say about their intentions and soft skills is subject to bias; only information derived from others or from direct observation (Boyatzis, 2018; Spencer and Spencer, 1993) of what people actually do when facing actual situations in the workplace can provide credible insights into the competencies that are exercised. For this reason, this study will not rely on subjective perceptions, but will focus on the concrete behaviors shown by data analysts and scientists.

In addition, the consolidated literature on behavioral competencies has provided, during recent decades, comprehensive and validated dictionaries of emotional competencies (the capability of being self-aware and managing one's internal emotional states, preferences and resources), social competencies (the capability of being aware of others' feelings, needs and concerns and of handling relationships and inducing desirable responses in others) and cognitive competencies (the capability of thinking or analyzing information and situations) (Boyatzis, 2009; Boyatzis and Sala, 2004). The investigation of data analysts' and scientists' behaviors using this broad and validated repertoire of competencies provides an opportunity to enrich the extant research with the salient skills for working in this fast-growing area. Consistently, in this study, we will code the competencies of data analysts and scientists against established dictionaries, as will be described in depth in the next section.

3. Research design

3.1 Sample

The study was conducted on a sample of 24 data scientists and data analysts operating in Italy, where the market for analytics has been growing at an average annual rate of 21.3% since 2015 (Politecnico di Milano, 2019). Italian companies are progressively introducing a data-driven culture: 93% of large companies and 62% of small and medium-sized enterprises (SMEs) invested in analytics projects during 2019. Consequently, these firms need to build their data science competencies and are hiring to fill dedicated roles. The greatest demand is for data analysts to operate mainly in large firms (76%) and in SMEs (23%), with an increase of 20% in the number of such roles between 2018 and 2019. Even data scientists have been progressively introduced to Italian companies; more commonly in large companies (49%) than in SMEs (16%) (Politecnico di Milano, 2019).

The sample was selected by searching through professional networks on LinkedIn. This search was conducted on the job title description and through snowball sampling where interviewees were asked to recommend other contacts for an interview (Flick *et al.*, 2004). In the analysis of the job profiles published in LinkedIn and in the preliminary contacts we had with the potential participants for our research, we collected information about their previous and current job positions, their related main tasks performed and their educational qualifications, to determine their professional experience. We compared the information gathered with the profile descriptions presented in the literature (Costa and Santos, 2017; Davenport, 2014; De Mauro *et al.*, 2019; Harris and Mehrotra, 2014; Verma *et al.*, 2019). Specifically, the sample was carefully selected on the basis of the following two criteria to reduce potential distortions: (1) the participants had to possess experience in the data analytics area, with daily work on reporting, strategic analysis and information system projects; and (2) they had to be involved in developing statistical analyses on large data sets to determine trends or develop business insights within their organizations.

This analysis generated a database of 130 potential interviewees. These individuals were contacted by the authors who provided information about the main goal of the research. A total of 24 professionals accepted the invitation to participate in the research. Table 3 summarizes the demographic and professional characteristics of the participants.

3.2 Data collection

The data were collected in 2018 by administering a semi-structured interview. The interviews were administrated by all authors (two interviewers for each interview) in-person or remotely

Coded participant role	Participant	Gender	Age	Organizational function	Education
Data scientist (11)	#1	Male	54	Business intelligence	High-school diploma
	#2	Male	28	IT	Master’s degree in physics
	#3	Male	42	Business technology	High-school diploma
	#4	Male	39	R&S	High-school diploma
	#5	Male	48	Business consultancy	Master’s degree
	#6	Female	41	Business and operation	Master’s degree in mathematics
	#7	Male	31	Digital and IT	Master’s degree in economics
	#8	Female	28	Business unit for digital marketing	Master’s degree in physics
	#9	Female	35	IT	PhD in physics
	#10	Male	29	Controller team	Master’s degree in mathematics
	#11	Male	29	Administration	PhD in physics
Data analyst (13)	#12	Female	24	IT	Bachelor degree in economics, statistics and finance
	#13	Male	37	Operations	Master’s degree in economics
	#14	Male	31	Research and development	Master’s degree in and informatics engineering
	#15	Male	56	Administration and control	Master’s degree in economics
	#16	Female	33	IT	Master’s degree in and informatics engineering
	#17	Female	30	Controlling	Master’s degree in mathematics
	#18	Male	50	Consultancy	PhD in evolutionary biology
	#19	Male	35	IT	Bachelor’s degree in statistics
	#20	Male	52	IT and sustainability	Master’s degree in cognitive science and sociology
	#21	Male	37	Project management	Master’s degree in economics
	#22	Female	37	SEO	Master’s degree in marketing
	#23	Male	34	Sales management	Bachelor’s degree in statistics
	#24	Male	38	Business analytics	Master’s degree in statistics

Table 3. Participants’ profiles

using videoconferencing applications. At the beginning of the interview, the interviewers illustrated the aim of the research and the administration of the interview. Then, in the first part of the interview, to distinguish data scientists from data analysts, the respondents were asked to provide a detailed description of their professional profile and some information about their companies (job title; description of duties and tasks in their current job position; seniority in their current organization; seniority related to their job title in other organizations; organizational function; education and certifications acquired to perform their job; span of control; firm industry and size). Specifically, the job characteristics identified in the literature and summarized in Table 1 were investigated for each participant.

In the second part of the interview, to delineate the competency profiles of the two roles, a behavioral event interview (hereafter BEI) was administered (Boyatzis, 1998; McClelland, 1973; Spencer and Spencer, 1993). BEI is a development of the critical incident interview technique (Flanagan, 1954) and was adapted using questions from a thematic apperception test, focusing on specific, salient events in the interviewee's life, according to the biodata method (Dailey, 1971). Each respondent was asked to recall five specific episodes that had occurred during the previous 12 months in which he/she had felt effective in performing his/her job, describing the context, the people involved, how he/she behaved and what he/she thought, felt and said. Before going into the detail of each episode/incident, the interviewee was asked to provide a brief overview of what led up to the episode, how he/she got involved, what the actual outcome was and how the episode made him/her feel effective. This allowed the interviewer to understand whether the episode fitted with the aim of the research and to assess if the episode represented a concrete event of job effectiveness.

The interviewers then asked for extensive narrations about how the respondents performed their tasks, how they made decisions and how they resolved critical issues. The interviewers investigated the specific behaviors and the underlying intent, guiding the interviewee with a set of probing questions (Boyatzis, 2009). For instance, when the respondent used the expression "Usually, I" or "Generally" in a sentence, the interviewer immediately asked for an example of when or what he or she actually did in the episode and what happened. If, during the narration of the episode, the interviewee referred to a collective action using the pronoun "we," he/she was invited to clarify who "we" were and to identify his/her contribution.

In total, 120 episodes were collected from the 24 respondents. Each interview – which lasted on average 1.5 h – was recorded and transcribed within one week for its subsequent coding.

3.3 Data analysis

The data analysis was conducted in several steps adopting a multimethod approach, which allowed the translation of the qualitative code derived from the thematic analysis into a numeric representation for the subsequent statistical elaborations (Boyatzis, 1998).

Initially, the three authors independently analyzed the job description provided by each participant during the first part of the interview and classified the participant into one of the two roles, looking at the type of data they worked with, their main tasks, the knowledge required and the tools adopted. Through discussion, the authors debated the classification of the participants and achieved agreement, identifying 13 data analysts and 11 data scientists. Subsequently, the authors presented the codification process to each participant and asked for confirmation about the classification of his/her role. All respondents agreed with the classification illustrated by the authors.

The authors then defined a codebook that they adopted for the coding of the behavioral competencies that emerged from the narrative data collected through the BEI. To do this, the existing competency dictionaries, which focus on the competencies needed to obtain effective results in different professional roles, were considered (such as Boyatzis, 1982; Dyer *et al.*, 2008; Puccio *et al.*, 2011; Spencer and Spencer, 1993). The authors then checked that the codebook obtained also encompassed the behavioral skills identified in the literature on analytics roles (such as Costa and Santos, 2017; Davenport and Patil, 2012; Harris and Mehrotra, 2014; Kim and Lee, 2016; Shirani, 2016; Vidgen *et al.*, 2017). The final codebook included 33 competencies, clustered into six thematic areas: awareness, action, social, cognitive, exploration and organizational action competencies, defined as follows. The *awareness* area includes competencies that allow individuals to understand themselves, other people and the organizational relationships. The *action* area refers to competencies that allow individuals to realize ideas, plans and solutions, and to work methodically and with initiative. The *social* area includes competencies that allow positive interaction with other people and help individuals to work with others effectively. The *cognitive* area embraces competencies that allow individuals to analyze and use information effectively to interpret phenomena or situations. The *exploratory* area concerns behaviors that individuals adopt to scan the world around them and to explore novel ideas. Finally, the *organizational action* area refers to behaviors activated for the interpretation of the competitive environment, the identification of business opportunities and the alignment of the individual's action to the organizational goals and priorities. Table 4 provides a definition of the competencies considered in this research. Because of the exploratory nature of this study, this broad repertoire of behavioral competencies derived from the literature

Cluster	Competency	Definition
Awareness	Self-awareness	Capacity to be in tune with your inner self, to evaluate the impact of emotions on your actions, to know your abilities and limits
	Empathy	Capacity to sense and accurately understand others' feelings and perspectives and take an active interest in their concerns
	Organizational awareness	Capacity to understand the relationships and the culture in an organization
Action	Efficiency orientation	Capacity to perceive input and output relationships with a concern for increasing the efficiency of actions
	Achievement orientation	Capacity to require high-quality standards to try to constantly improve your results, setting challenging and measurable goals, and measuring the progress made
	Resilience	Capacity to recover from adversity and respond to it positively by using personal resources
	Initiative	Capacity to act to accomplish something and to take this action prior to being asked or forced or provoked into it
	Change agent	Capacity to recognize the need for change, to promote and manage it
	Flexibility	Capacity to adapt oneself by modifying one's behavior in the face of changes, unexpected circumstances or different situations
	Self-control	Capacity to dominate emotions and impulses even in situations of stress or difficulty
	Accuracy	Capacity to develop the activities with precision and to check several times
	Risk-taking	Capacity to take a risk or to carry out an activity with an uncertain outcome
	Risk management	Capacity to identify in advance possible negative impacts of uncertain activities and contain losses
	Collection of information	Capacity to look for the correct information

(*continued*)

Table 4. Competency framework

Cluster	Competency	Definition
Social	Persuasion	Capacity to convince other people of the value of your point of view and to get their support
	Conflict management	Capacity to induce the parties in conflict to have a dialogue and identify solutions in which everyone can recognize themselves
	Teamwork	Capacity to stimulate the members of a group to work together effectively
	Developing others	Capacity to stimulate, support and provide resources for the improvement and growth of other people
	Networking	Capacity to create, maintain and use personal relationships to achieve goals
	Leadership	Capacity to lead others and trigger phenomena involving emotional resonance, to instill a sense of pride and inspire people through a compelling vision and to bring out their best aspects
	Customer focus	Capacity to understand other people's needs and pay attention to their satisfaction
Cognitive	System thinking	Capacity to break down complex problems and understand cause-and-effect relationships between the parties
	Diagnostic thinking	Capacity to conduct an accurate examination of the situation and describe the nature of the problem
	Pattern recognition	Capacity to recognize similarities among issues and make logical connections between concepts of different domains
	Lateral thinking	Capacity to try new ways of looking at problems and adopt unconventional perspectives
Exploration	Questioning	Capacity to formulate questions to gather information and challenge the current situation
	Observing	Capacity to observe the environment around you in different contexts with the aim of finding new ideas
	Experimenting	Capacity to explore new ideas through experiments and trials
Organizational action	Visionary thinking	Capacity to create and articulate a vivid future image of your group and/or organization and to define the actions and objectives necessary to achieve it
	Strategic thinking	Capacity to understand the strategic and competitive environment of the company
	Opportunity recognition	Capacity to perceive the opportunities emerging from the environment
	Commitment toward the group	Capacity to be responsible and to act for the good of the group
	Integrity	Capacity to be consistent with yourself

Table 4.

was considered to obtain an understanding of the behaviors most frequently mobilized by the individuals in the two roles when performing their jobs.

The next step of the analysis was the coding process. The transcribed interviews were coded independently by two of the authors to ensure reliability through multiple, independent data coding (Podsakoff *et al.*, 2003). Since each competency is a set of related but different behaviors organized around an underlying construct called the intent, the coders firstly detected the intent behind the behavior in each incident and subsequently codified the corresponding competency. For instance, for the competency "conflict management" the intent is to stimulate individuals or groups toward the resolution of a conflict, and this can be manifested through the following behavioral indicators: (1) when there is a conflict, the person helps to reduce the tension or de-escalate the conflict; (2) when there is a conflict, the person involves all parties in openly discussing the conflict with the intent of resolving it; or (3) when there is a conflict, the person identifies areas of mutual interest or benefit, or an objective to which all parties can aspire (Boyatzis, 1998). Inter-rater reliability estimates among the coders showed a high level of agreement (Cohen's kappa = 0.85). The authors examined and discussed their results until they reached 100% agreement.

To translate the qualitative observation of competencies into quantitative analysis (Boyatzis, 1998), a data set was constructed in which, for each participant and for each episode, the competencies were categorized as 1 if they were present in the episode, and 0 otherwise. Then, for each participant, the frequency of occurrence of each competency (Boyatzis, 1998; Cortellazzo *et al.*, 2020; Ryan *et al.*, 2009) was computed by calculating the number of episodes in which it occurred (with a minimum of zero and a maximum of five) normalized by the maximum number of episodes collected during the interview. Subsequently, a frequency distribution analysis was implemented and the Mann–Whitney U statistical test was performed to identify the distinctive competencies of data analysts and scientists. In the absence of a normal distribution of the variables, this non-parametric test has been adopted in the field of behavioral competencies and also applied in small samples (e.g. Camuffo *et al.*, 2012; Cortellazzo *et al.*, 2020). The statistic is derived from combining and ordering the scores for the two samples and then assigning ranks to them. The analysis between pairs aims to find out whether the two roles present significant differences in terms of the frequency of the manifestation of each behavioral competency considered.

4. Results

The first research question addressed by this study aimed to identify the behavioral competencies that data scientists and data analysts most frequently demonstrate when they effectively perform their job. The results of the frequency distribution analysis conducted on the overall sample are reported in Figure 1.

The results show that three competencies included in the awareness thematic area (*self-awareness*, *empathy* and *organizational awareness*) are among the skills most frequently activated by the interviewees.

Self-awareness is the first competency and the key component of the emotional and social intelligence framework (Goleman, 1998). It does not just encompass knowledge about oneself, but also includes an open and curious attitude about oneself, which is a prerequisite for developing an appropriate self-confidence that regulates our actions, orients our decision-making processes and directs our behaviors toward personal development. This competency seems to be crucial in analytics roles, since individuals in these roles are frequently exposed to emerging requests and non-routine tasks that challenge their skillset and stimulate their sense of purpose in their work. As shown in several of the interviews, both profiles show a strong self-awareness of their individual limits and points of mastery, in such a way as to prevent risky or troubling situations. For instance, Data scientist #8 who was developing a crucial project for a key national agency told us how, at a certain point, he decided to ask for back up and rely on more experienced colleagues to bring the project to a successful conclusion. In this way, he demonstrated that he could assess his own strengths and limits, but also his values, thoughts and emotions as they arose.

Besides *self-awareness*, the findings revealed that *social awareness* is often activated through the capacity to sense others' emotions and understand others' perspectives (*empathy*) and the capacity to recognize the values and culture of the members of a group (*organizational awareness*). During a long and much-debated transition from an old software system to a new one, Data analyst #13 recalled how he tried to understand why employees were resistant to change and were thus hampered in their progress in adapting to the new system. He observed the employees' behaviors, expressions and gestures about their issues with coping with the new software. He then understood their main struggles and found an effective way to

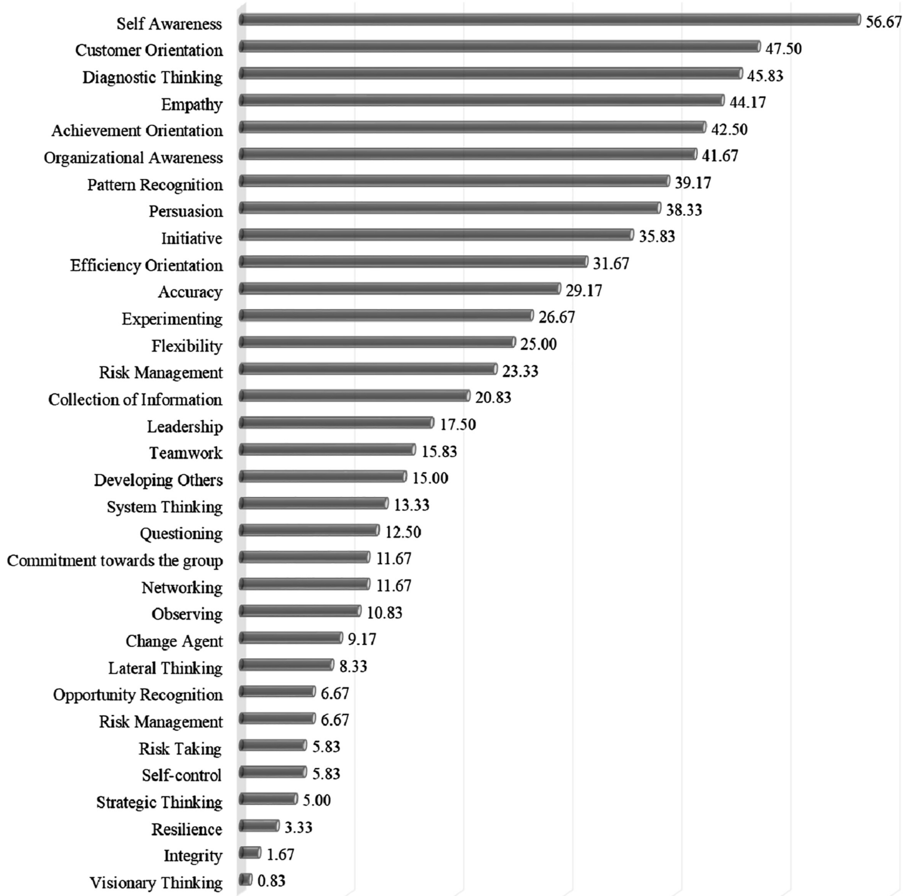

Figure 1.
Competencies according to the frequency of manifestation of the overall sample

collaborate with them and eventually to convince them to abandon the old tool and embrace the new one.

Moreover, matching the results of prior research, the findings show that individuals in these two roles frequently demonstrate *customer focus*, i.e. the social ability to understand other people's needs and pay attention to their satisfaction. Data analysts and scientists need to understand customers' needs and expectations, to develop the software, tools or analysis suitable for an organization. Whether the client is a bank or an online retail shop, periodic communication might be established so that the data analysts or scientists can acquire all the information that they need to integrate into their work.

Similarly, they demonstrate strong *diagnostic thinking*, namely, the cognitive ability to conduct an accurate examination of a situation and to describe the cause of a problem. Individuals in the two roles are shown to be highly skilled in examining data and in testing different hypotheses, and also in challenging complex issues and defining simpler scenarios to solve them.

Among the competencies included in the action area, the most frequently demonstrated is *achievement orientation*, through which data scientists and analysts adopt a growth mindset in addressing challenging problems that they face in their jobs. Both data scientists and data analysts experience failures, or moments in which data lead to a dead zone. However, our sample shows that both of them persevere, sticking to the project until the result is achieved.

Even though other behavioral competencies are demonstrated with a lower frequency, this does not imply that their impact on the results is less relevant, because the activation of the behaviors related to a competency also depends on the characteristics of the situations in which the interviewee operates. For instance, a lower frequency of the skills included in the organizational action area, such as *visionary thinking* and *strategic thinking*, can be explained by the characteristics of the decision-making processes of Italian companies, which are still highly centralized. Another explanation can be ascribed to the recent drive to embrace digitalization among Italian companies. Indeed, despite the common attempt to adopt a data-driven culture, top managers are still struggling to delegate the decision-making process in the analysis of the competitive environment to those in other roles such as data scientists or data analysts. It is only recently that these organizations have begun to create a data-driven culture, and analytics professionals devote most of their time to data preparation, analysis and presentation. Thus, less time remains for framing open-ended questions on the future of the business.

The second research question of this study aimed to detect the behavioral competencies that significantly distinguish data scientists from data analysts. A two-tailed Mann–Whitney U test was run to compare the frequency of the manifestation of each behavioral competency of the two profiles. The results, reported in Table 5, illustrate how certain specific emotional, social and cognitive competencies differentiate the role of a data scientist from that of a data analyst. Specifically, in the sample, data scientists more frequently demonstrated *self-awareness* and *teamwork* ($p < 0.05$), *networking*, *flexibility*, *system thinking* and *lateral thinking* ($p < 0.10$).

Data scientists demonstrated their *self-awareness* through a process of personal reflection that allowed them to gain a better understanding of how to approach a specific problem and of which knowledge and behaviors to mobilize. The data scientist's role is increasingly crucial in improving performance across different organizations and sectors. This role is often held by a team leader who carries out projects of various natures. Self-awareness, therefore, represents the most important competence, allowing data scientists to embark on complex projects and manage stressful situations, relying on their strong self-confidence.

As Participant #2 explained:

> Contrary to other people involved in the project, I knew that I had a 360-degree perspective on the problem. Thus, I felt myself able to communicate to the client both the technical and business requirements.

Teamwork and *networking* are two social competencies that also distinguish the profile of data scientists. *Teamwork* is the capacity to be respectful, collaborative and available to the group, inducing others to engage actively and enthusiastically in the common cause, reinforcing team spirit and encouraging the participation of all. It is common for data scientists to ask the effort of the entire team to import, clean, manipulate and also visualize and communicate data. Considering the versatile nature of their tasks and that their main objective is to provide actionable plans for organizations, the possibility of achieving positive, if not superior, outcomes increases when group effort comes into play.

A meaningful example is shown by Participant #3:

> Everyone [in the group] has his own technique but we were able to understand this issue working together, and it would not have been possible otherwise. One member of the group read all and she was able to tell us how things were done. I was more interested in understanding why this was done, and to understand the mathematical reasons. Another member of the group was much more interested in: "Eventually, why does it work in this way?" We are three very different personalities, but we started talking and everyone brought his own perspective and eventually we understood something new.

	Frequency data scientists	Frequency data analyst	z-values[1]	Sig.
Awareness competencies				
Self-awareness	69.1	46.2	2.048	**
Empathy	52.7	36.9	1.200	
Organizational awareness	41.8	41.5	0.153	
Action competencies				
Efficiency orientation	32.7	30.8	0.781	
Achievement orientation	50.9	35.4	1.364	
Resilience	5.5	1.53	1.255	
Initiative	32.7	38.5	0.753	
Change agent	9.1	9.2	0.471	
Flexibility	36.4	15.4	1.800	*
Self-control	7.3	4.6	0.699	
Accuracy	30.9	27.7	0.539	
Risk-taking	5.5	6.2	0.115	
Risk management	20.0	26.2	0.575	
Collection of information	20.0	21.5	0.000	
Social competencies				
Persuasion	40.0	36.9	0.061	
Conflict management	5.5	7.7	0.292	
Teamwork	25.5	7.7	2.349	**
Developing others	14.5	15.4	0.228	
Networking	16.4	7.7	1.912	*
Leadership	16.4	18.5	0.282	
Customer focus	52.7	43.1	1.411	
Cognitive competencies				
System thinking	20.0	7.7	1.948	*
Diagnostic thinking	40.0	50.8	0.933	
Pattern recognition	32.7	44.6	1.240	
Lateral thinking	12.7	4.6	1.815	*
Exploration competencies				
Questioning	18.2	7.7	1.439	
Observing	12.7	9.2	0.717	
Experimenting	30.9	23.1	0.877	
Organization action				
Visionary thinking	1.8	0	1.087	
Strategic thinking	0	9.2	1.663	*
Opportunity recognition	3.6	9.2	0.531	
Commitment toward the group	12.7	10.8	0.327	
Integrity	1.8	1.5	0.121	

Note(s): [1] Z-values from Mann–Whitney U Test. $*p < 0.10$; $**p < 0.05$ (two tailed)

Table 5.
Competency modeling: Mann–Whitney U test

Networking is the capacity to dedicate time and energy to the creation of new contacts with potentially interesting people and also to maintain and use these relationships to carry out work activities. As for teamwork, we noticed that data scientists use networking and connections, even outside the boundaries of the organization, to solve challenging issues in a sector that changes rapidly. Conferences, meetings and blogs are channels used by data scientists to keep themselves updated about new tools and software and also to build trusted relationships that can be used in the future.

Networking can be exemplified by the following quotes:

> I tried to collect information from as many people as possible. The majority of the work was done by asking external people how [. . .]. The remaining part was done by studying manuals and talking with other colleagues within the group (Participant #1).

> I had a colleague from another company who already knew this tool that I had to use in this project. I asked him to organize a couple of meetings to get acquainted with the technique (Participant #7).

Flexibility is another competency that distinguishes data scientists from data analysts. Data scientists are often asked to perform several tasks pertaining to the analytics domain. They also manage complex and large sets of data, in which the chance of errors or the need to integrate new data may occur frequently. Like any researcher, a data scientist needs to change his or her perspective, tools or approach and re-organize their work activities rapidly in the face of emerging requests, unexpected results from their analysis or changed circumstances. Furthermore, they are also involved in multiple projects at the same time for a vast array of sectors. Flexibility is, hence, crucial to develop quick, feasible and yet *ad hoc* solutions.

The following quote provides an example of this competency:

> In this project, I started the analysis of the data applying a traditional time series analysis technique, but I soon realized that it was not the effective model to deal with that type of data, since they presented a fast rate of change. Thus, I changed approach and related techniques (Participant #2).

Two cognitive competencies emerged as salient in the competency profile of data scientists, namely, *system thinking* and *lateral thinking*. The former refers to the capacity to break down problems and understand complex cause and effect relationships among parties. As Data scientist #9 explained, the identification of the root underlying cause of data might have a big impact on the project:

> The aim of the project was to optimize the application that brokers use. The users noticed that there were slowdowns which had caused major losses in the previous months due to a new application that had been installed. Timing is very important in the stock exchange environment. Reading the numbers, I noticed correlations between the data there should not have been. Thus, I analyzed in depth these correlations, in particular between the slowdowns and the number of users, the two things that should not be correlated, and I realized that this was due to an incorrect distribution of workloads.

Lateral thinking is the ability to think outside the box and to approach problems by adopting non-conventional logic. In view of their multiple tasks (such as mining, data delivery, the development of hypothesis-based analysis), lateral thinking helps data scientists to combine data in different ways and to find original solutions. Interestingly, the data scientist educational background was more diversified than that of the data analyst, suggesting that the former is more inclined to adopt a multidisciplinary perspective in their daily work activities.

As Data scientist #4 explained:

> In this project, I was in charge of the design and the implementation of a semantic tool for correlating information. Originally, the delivery of the tool to the clients was only conceived on-premises. I completely changed the logic and I proposed to my supervisor to offer the tool in the cloud.

In another episode, lateral thinking was demonstrated in the presentation of the results of an analysis:

> In the presentation meetings, usually people illustrate only the cases in which the tool can be effectively adopted. In that case, I did something that was atypical. I described the cases in which I cannot use that analytic tool, explaining the rationale behind this decision. This provided more useful and complete information to the audience (Participant #6).

Finally, it emerged from our analysis that one competency that clearly distinguishes data analysts from scientists is "strategic thinking." From the narratives collected during the interview, this competency does not refer to an understanding of the competitive environment of the company in which the data analyst operates. Instead, it is related to the customers' competitive landscape. Indeed, these professionals work closely with departments such as sales or product innovation, and they are requested to propose ad hoc analytics solutions that differentiate the clients' offering from the offerings of their competitors. The data analyst has to interpret what really matters to the organization, what the main value creation is and how to strategically transform this into a viable business solution.

The following quote of Data analyst #23 provides an example of this competency:

> I proposed to the sales manager to carry out, on the one hand, an analysis of the customer's account, to better understand its strengths and areas of improvement and, on the other hand, an external analysis of the various competitors, how they moved, how they presented themselves, how they offered their products, what keywords they used to describe them, what photos they posted. In so doing, I was able to present to the customer a proposal on how to work to optimize the account with the aim of increasing sales.

In summary, the aforementioned findings emphasize the complexity and the variety of behavioral competencies demonstrated by those working in these professional roles, with a focus not only on interpersonal and cognitive skills but also on emotional competencies. Moreover, it provides evidence of the commonalities between the two roles in terms of the competencies most frequently demonstrated, but also considers the main differences that distinguish the two profiles.

5. Discussion

5.1 Theoretical contribution

Our study advances the literature in defining the multifaceted nature of the intangible dimension of human capital in knowledge-intensive professions. It provides a conceptual framework that offers a holistic view on human capital by taking into consideration the role of behaviors. In particular, we unpacked this intangible/behavioral dimension into six categories (awareness, action, social, cognitive, exploration and organizational action competencies) that are equally important in creating unique and difficult-to-imitate skills that produce competitive advantage for the company. The development and the application of this framework in a sample of data scientists and analysts shed new light on the successful role played by the behavioral competencies activated by these professionals in performing their jobs and on their variety.

The study provides a more fine-grained definition of the two roles and enriches the repertoire of competencies that had been considered until now in the literature. Specifically, it offers further evidence of the importance of emotional, interpersonal and cognitive competencies for both profiles, advancing the anecdotal evidence and the results of the analysis of job advertisements and LinkedIn profiles found in prior research (De Mauro *et al.*, 2019; Ecleo and Galido, 2017; Verma *et al.*, 2019). Indeed, contrary to the aforementioned studies, this research shows that awareness competencies seem to assume a critical role in enabling data scientists and analysts to perform their jobs effectively. These professionals do not work in silos: instead, they perform their tasks within projects and spend several hours a week in meetings with internal and external stakeholders (King and Magoulas, 2016; Suda, 2018). Therefore, understanding others' points of view (empathy) and being aware of the informal rules and of the key power relationships that characterize an organizational context (organizational awareness) becomes crucial to address problems effectively and provide effective solutions.

Moreover, the real-life experiences collected through BEI also demonstrated the high frequency of the manifestation of action competencies, with specific regard to achievement orientation and initiative for both profiles. Flexibility, which in a previous study (Kim and

Lee, 2016) was associated with the data scientist's profile, turned out to distinguish this role from that of a data analyst.

A further contribution lies in the identification of those social and cognitive competencies, which distinguish the two profiles. These competencies have been already mentioned in prior research (Costa and Santos, 2017; Davenport and Patil, 2012; Kim and Lee, 2016; Shirani, 2016; Verma *et al.*, 2019), but no clear indication has been provided in terms of those distinctive competencies that characterize the two profiles. Concerning social competencies, this study demonstrates that persuasion and customer orientation are frequently activated by both profiles, but, for data scientists, teamwork and networking are also distinctive in performing their job effectively. As emerged from the episodes analyzed, this can be explained by the fact that data scientists are asked to cooperate with different departments and stakeholders within and across organizational boundaries. Moreover, the rate of technological change that characterizes the analytics field spurs these professionals to keep themselves up to date on recent advances and to search for solutions for technical problems, relying on their networks of contacts inside and outside the working context. Besides the relevance of diagnostic thinking for both profiles, the analysis of cognitive competencies also emphasizes the differences between the two roles: data scientists are required, more frequently than data analysts, to interpret phenomena and situations effectively, by identifying complex cause and effect relationships (system thinking) and by adopting unusual and creative perspectives (lateral thinking).

Finally, this study provides a methodological contribution to the literature, which investigates the competency profile of knowledge-intensive professions relying on self-perception measures and employers' expected skillsets reported in job postings. Unlike prior research, we represented the intangible component of human capital adopting the "stream 4" or the behavioral level of emotional intelligence (Boyatzis, 2018), which enables the detection of the behaviors activated by a person in his/her work environment, mitigating the possible biases and unreliable responses associated with self-assessment (Dunning *et al.*, 2004).

5.2 Implications for practice

Our findings offer interesting insights that can be evaluated at the educational and organizational levels. A first implication is for educational institutions, which could use this study to design better curricula for entry-level data scientists and analysts. As demand for these profiles is expected to increase in the future, educational institutions face the challenge of providing adequate answers to the skills shortage for these roles. Indeed, despite the increasing academic offerings of dedicated programs, the shortage of analytical and data science skills continues to represent a critical constraint (LinkedIn, 2018; McKinsey Global Institute, 2016). The skill gap refers not only to technical competencies but also to soft skills, which are rarely included in higher educational programs (Bowers *et al.*, 2018) for these roles. This can be explained by the fact that the development of behavioral competencies and the development of technical skills require different teaching methods, affecting the facilitating role of the instructor, the experimental learning approach and the design of training tools tailored for the specific competency, to cite just a few (Bedwell *et al.*, 2014). Other factors that seem to limit the inclusion of dedicated behavioral competency courses in data science and analytics programs are: (1) the lack of awareness among the faculty members in charge of designing degree programs of the required behavioral competencies for these professional roles; (2) the adoption of a technologically oriented approach in designing educational programs, to equip students with the most recent advances in tools and techniques in the analytics realm; and (3) the presence of credit hours limits, which makes it difficult to choose to leave a technical course out of the program in favor of one devoted to soft skills development (Bowers *et al.*, 2018). Higher education institutions are asked to overcome these obstacles by including dedicated learning experiences in their programs (e.g. in the form of courses or seminars) that allow future data analysts or scientists to: (1) become aware of the importance of behavioral competencies for their profession, with an emphasis on those soft skills that they are expected to manifest most frequently in the workplace; and (2) acquire the methodology to develop behavioral competencies, tailoring the techniques according to the specific skill. A methodological approach to competency development, which has been implemented in the academic context and has demonstrated positive and enduring learning outcomes, is the process of intentional change for skills development (Boyatzis, 2006; Boyatzis and Saatcioglu, 2008; Boyatzis *et al.*, 2002).

Moreover, this study can inspire human resources management specialists to improve their recruitment processes for these data analytics roles. The most frequently manifested competencies demonstrated by data analysts and scientists in this study can provide a guide for recruiters. Specifically, these competencies have to be indicated explicitly in the job description and in job advertisements, to orient candidates' applications. This can also help to overcome the bias that affects data analytics professionals, who are often seen only as numerically minded individuals. Moreover, recruiters can be trained in adopting behavioral event interviews to assess candidates' level of mastery of the required behavioral competencies. A relevant role in promoting individual behaviors coherent with the role's requirements is played by the induction program, in which the behavioral competency profile should be made explicit; through periodic feedback, data analysts and scientists can redirect their behaviors to meet the job and company expectations better. Finally, considering the skills shortages suffered by data scientists and analysts in their jobs, competency-based training experience should be designed and implemented. In this regard, the aforementioned methodology of the intentional change process has been demonstrated to induce long-lasting change in the behavioral competency profile of individuals, unlike the majority of soft skills training experiences, which are characterized by the so-called "honeymoon effect" (Boyatzis, 2006).

5.3 Limitations and future lines of research

This study presents a number of limitations that are also elements for future research. First, the study applies the competency framework on a sample of data analysts and data scientists operating in the Italian context. It would be beneficial to enlarge the sample and to replicate this study involving these two professional roles from different geographical areas and cultural contexts, to confirm the validity of the results and increase the analytic generalizability of this exploratory study. In the same vein, the validated framework – in which 33 competences are listed, described and clustered into six thematic areas – could be replicated in other studies considering other knowledge-intensive professions relevant in the digital age (Ciarli *et al.*, 2020).

Second, in line with the theory on action and performance (Boyatzis, 1982), a further line of future research would be to consider the characteristics of the organizational context in which data scientists and analysts operate and investigate the factors that may facilitate or hamper the activation of specific behavioral competencies. Indeed, behavioral competencies are activated to match the characteristics of the situations that the role holder faces in the workplace, and the organizational environment may also explain the differences in the manifestation of exploratory and strategic competencies, that might be influenced by different levels of decentralization, organizational flatness, leadership styles or firm dimension. Finally, a promising line of research concerns the relationship between the manifestation of behavioral competencies and individual performance. It would be valuable to identify the workplace performance metrics associated with these professional profiles and adopt them as criteria for sampling the participants of the study, making it possible to compare the behavioral competencies most frequently demonstrated by outstanding performers against those manifested by average performers (Spencer and Spencer, 1993). This kind of differentiation would provide valuable insights about those behavioral competencies that make a data scientist or a data analyst a vital asset for a company.

Note

1. We counted more than 20 courses offered only by Coursera, which is one of the more established and internationally known platform. These courses are grouped under the label "data science" and offer classes and specialization courses to learn the fundamentals of interpreting data, performing analysis and how to communicate results (https://www.coursera.org/browse/data-science, information retrieved on April 1, 2021).

References

Ashkanasy, N.M. and Daus, C.S. (2005), "Rumors of the death of emotional intelligence in organizational behavior are vastly exaggerated", *Journal of Organizational Behavior*, Vol. 26 No. 4, pp. 441-452, doi: 10.1002/job.320.

Barney, J.B. (1991), "Firm resources and sustained competitive advantage", *Journal of Management*, Vol. 17 No. 1, pp. 99-120, doi: 10.1177/014920639101700108.

Beck, M. and Libert, B. (2017), "The rise of AI makes emotional intelligence more important", *Harvard Business Review*, 15 February, available at: https://hbr.org/2017/02/the-rise-of-ai-makes-emotional-intelligence-more-important.

Becker, G.S. (1993), *Human Capital*, The University of Chicago Press, Chicago, London.

Bedwell, W.L., Fiore, S.M. and Salas, E. (2014), "Developing the future workforce: an approach for integrating interpersonal skills into the MBA classroom", *Academy of Management Learning and Education*, Vol. 13 No. 2, pp. 171-186, doi: 10.5465/amle.2011.0138.

Bonesso, S., Gerli, F., Pizzi, C. and Boyatzis, R.E. (2020), "The role of intangible human capital in innovation diversification: linking behavioral competencies with different types of innovation", *Industrial and Corporate Change*, Vol. 28 No. 3, pp. 661-681, doi: 10.1093/icc/dtz062.

Bowers, M.R., Camm, J.D. and Chakraborty, G. (2018), "The evolution of analytics and implications for industry and academic programs", *INFORMS Journal on Applied Analytics*, Vol. 48 No. 6, pp. 487-499, doi: 10.1287/inte.2018.0955.

Boyatzis, R.E. and Goleman, D. (2007), *Emotional Competency Inventory*, The Hay Group, Boston.

Boyatzis, R.E. and Saatcioglu, A. (2008), "A 20-year view of trying to develop emotional, social and cognitive intelligence competencies in graduate management education", *Journal of Management Development*, Vol. 27 No. 1, pp. 92-108, doi: 10.1108/02621710810840785.

Boyatzis, R.E. and Sala, F. (2004), "Assessing emotional intelligence competencies", in Geher, G. (Ed.), *The Measurement of Emotional Intelligence, Hauppauge*, Science Publishers, NY, Novas, pp. 147-180.

Boyatzis, R.E., Stubbs, E.C. and Taylor, S. (2002), "Learning cognitive and emotional intelligence competencies through graduate management education", *Academy of Management Learning and Education*, Vol. 1 No. 2, pp. 150-162, doi: 10.5465/AMLE.2002.8509345.

Boyatzis, R.E. (1982), *The Competent Manager: A Model for Effective Performance*, Wiley-Interscience, New York, NY.

Boyatzis, R.E. (1998), *Transforming Qualitative Information*, Sage Publications, Thousand Oaks.

Boyatzis, R.E. (2006), "An overview of intentional change from a complexity perspective", *Journal of Management Development*, Vol. 25 No. 7, pp. 607-623, doi: 10.1108/02621710610678445.

Boyatzis, R.E. (2008), "Competencies in the 21st century", *Journal of Management Development*, Vol. 27 No. 1, pp. 5-12, doi: 10.1108/02621710810840730.

Boyatzis, R.E. (2009), "Competencies as a behavioral approach to emotional intelligence", *Journal of Management Development*, Vol. 28 No. 9, pp. 749-770, doi: 10.1108/02621710910987647.

Boyatzis, R.E. (2018), "The behavioral level of emotional intelligence and its measurement", *Frontiers Psychology*, Vol. 9 No. 1438, pp. 1-12, doi: 10.3389/fpsyg.2018.01438.

Camuffo, A., Gerli, F. and Gubitta, P. (2012), "Competencies matter: modeling effective entrepreneurship in northeast of Italy small firms", *Cross Cultural Management*, Vol. 19 No. 1, pp. 48-66, doi: 10.1108/13527601211195628.

Capgemini (2019), "Emotional intelligence. The essential skillset for the age of AI", available at: https://www.capgemini.com/it-it/research/emotional-intelligence/ (accessed 16 November 2019).

Cherniss, C. (2010), "Emotional intelligence: toward clarification of a concept", *Industrial and Organizational Psychology*, Vol. 3 No. 2, pp. 110-126, doi: 10.1111/j.1754-9434.2010.01231.x.

Ciarli, T., Kenney, M., Massini, S. and Piscitello, L. (2020), "Digital technologies, innovation, and skills: emerging trajectories and challenges", *Research Policy*, Vol. 50 No. 7, p. 104289, doi: 10.1016/j.respol.2021.104289.

Cortellazzo, L., Bonesso, S. and Gerli, F. (2020), "Entrepreneurs' behavioural competencies for internationalisation: exploratory insights from the Italian context", *International Journal of Entrepreneurial Behaviour and Research*, Vol. 26 No. 4, pp. 723-747, doi: 10.1108/IJEBR-12-2018-0806.

Costa, C. and Santos, M.Y. (2017), "The data scientist profile and its representativeness in the European e-Competency framework and the skills framework for the information age", *International Journal of Information Management*, Vol. 37 No. 6, pp. 726-734, doi: 10.1016/j.ijinfomgt.2017.07.010.

Dailey, C.A. (1971), *Assessment of Lives: Personality Evaluation in a Bureaucratic Society*, Jossey-Bass, San Francisco, CA.

Davenport, T. and Harris, J. (2017), *Competing on Analytics*, Harvard Business Review Press, Boston, Massachusetts.

Davenport, T.H. and Patil, D.J. (2012), "Data scientist: the sexiest job of the 21st century", *Harvard Business Review*, Vol. 90, October 2012, pp. 70-76.

Davenport, T.H. (2014), *Big Data at Work: Dispelling the Myths, Uncovering the Opportunities*, Harvard Business Review Press, Boston, Massachusetts.

De Mauro, A., Greco, M. and Grimaldi, M. (2019), "Understanding big data through a systematic literature review: the ITMI model", *International Journal of Information Technology and Decision Making*, Vol. 18 No. 4, pp. 1433-1461, doi: 10.1142/S0219622019300040.

Dong, T. and Triche, J. (2020), "Longitudinal analysis of job skills for entry-level data analysts", *Journal of Information Systems Education*, Vol. 31 No. 4, pp. 312-326, available at: https://aisel.aisnet.org/jise/vol31/iss4/6.

Dubey, R.S. and Tiwari, V. (2020), "Operationalisation of soft skill attributes and determining the existing gap in novice ICT professionals", *International Journal of Information Management*, Vol. 50, pp. 375-386, doi: 10.1016/j.ijinfomgt.2019.09.006.

Dunning, D., Heath, C. and Suls, J.M. (2004), "Flawed self-assessment implications for health, education, and the workplace", *Psychological Science in the Public Interest*, Vol. 5 No. 3, pp. 69-106, doi: 10.1111/j.1529-1006.2004.00018.x.

Dyer, J.H., Gregersen, H.B. and Christensen, C. (2008), "Risk and rationality in entrepreneurial processes", *Strategic Entrepreneurship Journal*, Vol. 2, pp. 317-338, doi: 10.1002/sej.59.

Ecleo, J.J. and Galido, A. (2017), "Surveying LinkedIn profiles of data scientists: the case of the Philippines", *Procedia Computer Science*, Vol. 127, pp. 53-60, doi: 10.1016/j.procs.2017.12.129.

Flanagan, J.C. (1954), "The critical incident technique", *Psychological Bulletin*, Vol. 51 No. 4, pp. 327-358, doi: 10.1037/h0061470.

Flick, U., Steinke, I. and von Kardoff, E. (2004), *A Companion to Qualitative Research*, Sage Publications, London.

Gandomi, A. and Haider, T.M. (2015), "Beyond the hype: big data concepts, methods, and analytics", *International Journal of Information Management*, Vol. 35 No. 2, pp. 137-144, doi: 10.1016/j.ijinfomgt.2014.10.007.

Goleman, D. (1998), *Working with Emotional Intelligence*, Bantam Books, New York, NY.

Granville, V. (2014), *Developing Analytics Talent. Becoming a Data Scientist*, Wiley, Indianapolis.

Gutierrez, B., Spencer, S. and Zhu, G. (2012), "Thinking globally, leading in Chinese, Indian and Western leadership", *Journal of Cross-Cultural Management*, Vol. 19 No. 1, pp. 67-89, doi: 10.1108/13527601211195637.

Harris, J.G. and Mehrotra, V. (2014), "Getting value from your data scientists", *MIT Sloan Management Review*, Vol. 56 No. 1, pp. 15-18.

Hitt, M.A., Bierman, L., Shimizu, K. and Kochhar, R. (2001), "Direct and moderating effects of human capital on strategy and performance in professional service firms: a resource-based perspective", *Academy of Management Journal*, Vol. 44 No. 1, pp. 13-28, doi: 10.2307/3069334.

Hoover, J.D., Giambatista, R.C., Sorenson, R.L. and Bommer, W.H. (2010), "Assessing the effectiveness of whole person learning pedagogy in skill acquisition", *Academy of Management Learning and Education*, Vol. 9 No. 2, pp. 192-203, doi: 10.5465/amle.9.2.zqr192.

Hopkins, M.M., O'Neil, D.A. and Stoller, J.K. (2015), "Distinguishing competencies of effective physician leaders", *Journal of Management Development*, Vol. 34 No. 5, pp. 566-584, doi: 10.1108/JMD-02-2014-0021.

Kim, J.Y. and Lee, C.K. (2016), "An empirical analysis of requirements for data scientists using online job postings", *International Journal of Software Engineering and Its Applications*, Vol. 10 No. 4, pp. 61-172.

King, J. and Magoulas, R. (2016), *2016 Data Science Salary Survey Tools, Trends, what Pays (And what Doesn't) for Data Professionals*, O'Reilly Media, Sebastopol, California.

Kolb, D.A. (2015), *Experiential Learning: Experience as the Source of Learning and Development*, Pearson, London.

Lee, C. and Han, H. (2008), "Analysis of skills requirement for entry-level programmer/analysts in Fortune 500 corporations", *Journal of Information Systems Education*, Vol. 19 No. 1, pp. 17-27, available at: https://aisel.aisnet.org/jise/vol19/iss1/3.

LinkedIn (2018), "Workforce report December 2018", available at: https://economicgraph.linkedin.com/resources/linkedin-workforce-report-december-2018 (accessed 15 March 2021).

LinkedIn (2019), "The most promising jobs of 2019", available at: https://blog.linkedin.com/2019/january/10/linkedins-most-promising-jobs-of-2019 (accessed 16 June 2019).

LinkedIn (2020), "Emerging jobs report", available at: https://business.linkedin.com/content/dam/me/business/en-us/talent-solutions/emerging-jobs-report/Emerging_Jobs_Report_U.S._FINAL.pdf (accessed 30 November 2020).

Lorenz, M., M., Rüßmann, R., Strack, K.L., Lueth, K.L. and Bolle, M. (2015), *Man and Machine in Industry 4.0. How Will Technology Transform the Industrial Workforce through 2025?*, The Boston Consulting Group, Massachusetts, available at: https://www.bcgperspectives.com/content/articles/technology-business-transformation-engineered-products-infrastructure-man-machine-industry-4 (accessed 30 November 2020).

McClelland, D.C. (1951), *Personality*, William Sloane Associates, New York, NY.

McClelland, D.C. (1973), "Testing for competency rather than for 'intelligence'", *American Psychologist*, Vol. 28, pp. 1-14, doi: 10.1037/h0034092.

McEnrue, M.P. and Groves, K. (2006), "Choosing among tests of emotional intelligence: what is the evidence?", *Human Resource Development Quarterly*, Vol. 17 No. 1, pp. 9-42, doi: 10.1002/hrdq.1159.

McGuirk, H., Lenihan, H. and Hart, M. (2015), "Measuring the impact of innovative human capital on small firms' propensity to innovate", *Research Policy*, Vol. 44 No. 4, pp. 965-976, doi: 10.1016/j.respol.2014.11.008.

McKinsey Global Institute (2016), "The age of analytics: competing in a data-driven world", available at: https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-age-of-analytics-competing-in-a-data-driven-world (accessed 18 June 2019).

Mitchell, R.B., Woolridge, R.W. and Johnson, V. (2021), "The role of nontechnical skills in providing value in analytics-based decision culture", *Journal of Education for Business*, Vol. 96 No. 1, pp. 1-9, doi: 10.1080/08832323.2020.1719961.

Ozkan-Ozen, Y.D. and Kazancoglu, Y. (2021), "Analysing workforce development challenges in the Industry 4.0", *International Journal of Manpower*, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/IJM-03-2021-0167.

Podsakoff, P.M., MacKenzie, S.M., Lee, J. and Podsakoff, N.P. (2003), "Common method variance in behavioural research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88, pp. 879-903, doi: 10.1037/0021-9010.88.5.879.

Politecnico di Milano (2019), "Osservatorio big data analytics and business intelligence strategic data science: time to grow up!", available at: https://www.som.polimi.it/event/osservatorio-big-data-analytics-bi-191119/ (accessed 20 December 2019).

Puccio, G.J., Mance, M. and Murdock, M.C. (2011), *Creative Leadership: Skills that Drive Change*, Sage Publications, Los Angeles.

Ryan, G., Emmerling, R.J. and Spencer, L.M. (2009), "Distinguishing high-performing European executives", *Journal of Management Development*, Vol. 28 No. 9, pp. 859-875, doi: 10.1108/02621710910987692.

Shirani, A. (2016), "Identifying data science and analytics competencies based on industry demand", *Issues in Information Systems*, Vol. 17 No. 4, pp. 137-144, doi: 10.48009/4_iis_2016_137-144.

Singh, R.K., Agrawal, S. and Modgil, S. (2021), "Developing human capital 4.0 in emerging economies: an industry 4.0 perspective", *International Journal of Manpower*, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/IJM-03-2021-0159.

Škrinjarić, B. and Domadenik, P. (2020), "Examining the role of key competences in firm performance", *International Journal of Manpower*, Vol. 41 No. 4, pp. 391-416, doi: 10.1108/IJM-10-2018-0349.

Spencer, L.M. and Spencer, S.M. (1993), *Competency at Work. Models for Superior Performance*, John Wiley & Sons, New York, NY.

Suda, B. (2018), *2017 Data Science Salary Survey*, O'Reilly Media, Sebastopol, California.

Sweetland, S.R. (1996), "Human capital theory: foundations of a field of Inquiry", *Review of Educational Research*, Vol. 66 No. 3, pp. 341-359, doi: 10.3102/00346543066003341.

Unger, J.M., Rauch, A., Frese, M. and Rosenbusch, N. (2011), "Human capital and entrepreneurial success: a meta-analytical review", *Journal of Business Venturing*, Vol. 26 No. 3, pp. 341-358, doi: 10.1016/j.jbusvent.2009.09.004.

Verma, A., Yurov, K.M., Lane, P.L. and Yurova, Y.V. (2019), "An investigation of skill requirements for business and data analytics positions: a content analysis of job advertisements", *Journal of Education for Business*, Vol. 94 No. 4, pp. 243-250, doi: 10.1080/08832323.2018.1520685.

Vidgen, R., Shaw, S. and Grant, D.B. (2017), "Management challenges in creating value from business analytics", *European Journal of Operational Research*, Vol. 261 No. 2, pp. 626-639, doi: 10.1016/j.ejor.2017.02.023.

Vidotto, J.D.F., Ferenhof, H.A., Selig, P.M. and Bastos, R.C. (2017), "A human capital measurement scale", *Journal of Intellectual Capital*, Vol. 18 No. 2, pp. 316-329, doi: 10.1108/JIC-08-2016-0085.

World Economic Forum (2020), "The future of jobs report 2020", available at: http://www3.weforum.org/docs/WEF_Future_of_Jobs_2020.pdf (accessed 20 November 2020).

Wright, P.M. and McMahan, G.C. (2011), "Exploring human capital: putting 'human' back into strategic human resource management", *Human Resource Management Journal*, Vol. 21 No. 2, pp. 93-104, doi: 10.1111/j.1748-8583.2010.00165.x.

Yammarino, F.J. and Atwater, L.E. (1993), "Understanding self-perception accuracy: implication for human resource management", *Human Resource Management*, Vol. 32 Nos 2 and 3, pp. 231-247, doi: 10.1002/hrm.3930320204.

About the authors

Sara Bonesso is an Associate Professor of Business Organization and Human Resources Management at the Department of Management, Ca' Foscari University of Venice, where she received her PhD in Management. She is also the Vice-director of the Ca' Foscari Competency Centre. Her research interests lie in the fields of organizational behavior and human resources management. Her recent research investigates the development of emotional and social competencies, the impact of behavioral competencies on entrepreneurial intent, innovation, digital transformation, employability and career development. Sara Bonesso is the corresponding author and can be contacted at: bonesso@unive.it

Fabrizio Gerli is an Associate Professor of Business Organization and Human Resources Management at the Department of Management, Ca' Foscari University of Venice, where he received his PhD in Management. He is the director of the Ca' Foscari Competency Centre and Scientific Coordinator of postgraduate courses in Human Resources Management. His research interests focus on inter-firm and inter-industry competency modelling, entrepreneurial competencies and firm performance, development of behavioral competencies.

Elena Bruni is a Marie Skłodowska-Curie Fellow at the WU Vienna University. Former Post-Doc Research Fellow at the Cà Foscari University, Department of Management. Her research interests lie in the fields of organizational behavior and human resources management. Her current research interests revolve around organization theory, framing, and discourse. In particular, these topics involve questions of how different modes of language (visual and written) mobilize collective action.