Bus Inf Syst Eng 58(3):213–231 (2016)
DOI 10.1007/s12599-016-0428-2

RESEARCH PAPER

The Role of Gender in Business Process Management Competence Supply

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Received: 1 May 2015 / Accepted: 28 January 2016 / Published online: 7 March 2016

Abstract While Business Process Management (BPM) was originally focused on Information Technology as a key factor driving the efficiency and effectiveness of organizational processes, there is now a growing consensus among practitioners and academics that BPM represents a holistic management approach that also takes such factors as corporate governance, human capital, and organizational culture into account. Studies show that the BPM practice faces a shortage of competence supply that stems from a shortage of qualified BPM professionals. At the same time, there is a distinct underrepresentation of women in technology-related fields; it has been suggested that gender stereotypes are one of the reasons for this underrepresentation. The goal of this research paper is, thus, to better understand the role of gender in the BPM competences supply. In this study 10,405 LinkedIn profiles of BPM professionals were analyzed using a text mining technique called Latent Semantic Analysis. Twelve distinct categories of supplied BPM competences were identified and it was investigated how far gender biases exist among BPM professionals. The nature of BPM-related competences is discussed, together with the differences in their presentation by male and female professionals, which indicate potential existence of gender stereotypes. Further, it is discussed how the apparent underrepresentation of women among BPM professionals can be addressed to close the competence gap in the field. The study contributes to both the call for research on human capital in the BPM field, and the calls for research on gender and gender stereotypes in technology-related fields.

Keywords Business process management · Competences · Skills · Latent semantic analysis · Text mining · Gender diversity · BPM workforce

This manuscript is an extended and revised version of a conference paper of the same authors presented at the 23rd European Conference on Information Systems (ECIS 2015), which was selected by the editorial board of the ECIS 2015 Special Issue of the BISE (Business and Information Systems Engineering) journal for a fast-track review process.

Accepted after two revisions by the editors of the special issue.

Electronic supplementary material The online version of this article (doi:10.1007/s12599-016-0428-2) contains supplementary material, which is available to authorized users.

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1 Introduction

Business Process Management (BPM) refers to the design, implementation, continuous improvement, and innovation of organizational processes (e.g., Dumas et al. 2013; vom Brocke and Rosemann 2015). According to Gartner's Chief Information Officers (CIO) studies, the improvement of a company's business processes has remained one of the top business priorities of Information Technology (IT) executives for almost a decade (Gartner 2011).

In the early days, BPM used to focus on IT-enabled opportunities to radically redesign a company's business processes (Altinkemer et al. 2011; Hammer 2015). However, the understanding of BPM has, in recent years, developed into a more holistic management philosophy (Gartner 2014a) that also considers factors beyond IT – like corporate governance, human capital, or corporate culture (Rosemann and vom Brocke 2015). Nevertheless, extant BPM research still largely focuses on technical aspects, such as process modeling, process automation, or process mining (e.g., Dumas et al. 2013; Schmiedel et al. 2014). At the same time, scholars claim that critical success factors of BPM projects are found to be mostly non-technical (e.g., Trkman 2010), and therefore call for more research into non-technical aspects, such as the role of human capital in the BPM field (Rosemann et al. 2006; Kokkonen 2014).

In line with today's holistic understanding of BPM in academia, companies are aware that BPM projects require a range of competences provided by a variety of professionals (Lee et al. 2000; Müller et al. 2014). At the same time, several academic studies have shown that there is a shortage of BPM competence supply in practice, stemming from a shortage of qualified BPM professionals (Bandara et al. 2010; Antonucci and Goeke 2011). Also industry studies found that it is hard for companies to find enough qualified employees (the *quantity* aspect) to fill the open positions in particular BPM areas (Gartner 2013). Furthermore, employees already working in the field often lack the required competences (the *quality* aspect) for conducting successful BPM implementations (Gartner 2008; Bandara et al. 2010).

Significantly, not only is there this shortage of people and competences, there is also a noticeable underrepresentation of women in technology-related fields (e.g., Camp 2012; Clayton et al. 2012), such as BPM. This phenomenon has been acknowledged in numerous studies (e.g., von Hellens et al. 2012; Trauth 2013), as well as it is being indicated by both statistics on the gender distribution among IT employees in Western societies (Australian Workforce and Productivity Agency 2013; e-Skills UK 2014; NCWIT 2014) and among students of technical study programmes at universities (Australian Computer Society 2012; European Commission 2012; VCAA Statistics 2013). Thus, in technology-related professions the potential of women, who form half of the population, remains largely untapped. This has far-reaching negative consequences for the IT workforce, and, therefore, needs to be further addressed in research and practice (e.g., Ahuja and Thatcher 2005; Craig 2015).

Scholars claim that the existence of gender stereotypes about competences in technology-related fields is one of the reasons for the underrepresentation of women in these fields (e.g., Wajcman 1991; Robertson et al. 2001; Wilson 2004; Bayer Corporation 2010; Ashcraft et al. 2012). There is, thus, a call for the investigation of these gender stereotypes in order to tackle them (Trauth et al. 2012, 2015). Up to now, there have been no studies examining potential gender stereotypes in the context of BPM, although gaining such insights could contribute to addressing the competence gap in the field. Against this background, *the goal of this study is to understand the role of gender in BPM competence supply*. Accordingly, our study contributes to both the call for research on human capital in the BPM field, and the calls for research on gender and gender stereotypes in technology-related fields.

In order to address the study goal, we use Latent Semantic Analysis (LSA), a text mining technique, to analyze 10,405 profiles of BPM professionals published on LinkedIn (http://www.linkedin.com), "the world's largest professional online social network" (Bastian et al. 2014, p. 1). Our main focus is on examining and comparing the competences presented by male and female BPM specialists. In particular, we identify the most typical categories of BPM competences and investigate how far gender biases exist among professionals representing each category. Additional analyses include the comparison of profiles of male and female BPM professionals with regard to current positions, work experience, endorsements, and connections.

The remainder of the paper is structured as follows. In the next section, we provide an overview of related studies on BPM competences and theoretical approaches to gender and technology (Sect. 2). Then we justify the appropriateness of using LinkedIn profiles as a data source for our study, as well as describe the processes of profile extraction, data pre-processing, and LSA (Sect. 3). The empirical results of our analysis, including the identified categories of supplied BPM competences, as well as the comparison of online profiles of male and female BPM professionals are included in the next section (Sect. 4), and overall results are discussed in the subsequent section (Sect. 5). Finally, this study's outcomes and limitations, as well as areas of future research are summarized (Sect. 6).

2 Research Background

This section provides an overview of the research that our study builds upon, including insights into existing research on individual competences in the BPM field and theoretical approaches to studying gender and technology.

2.1 Research on Competences in the Business Process Management Field

In our study, we understand the term *competence* to be a combination of abilities, work-related knowledge, and skills held by an individual (Nordhaug 1993). Although in empirical studies the terms *ability, knowledge*, and *skill* are often used interchangeably, we acknowledge their different connotations and follow the definitions provided by Müller et al. (2014). Abilities are attributes considered innate to an individual (e.g., a person's ability for logical reasoning); knowledge is a theoretical understanding of a concept (e.g., the meaning of the term *business process*); and skill is the practical application of that knowledge (e.g., how to identify deficiencies in business processes).

Extant studies on BPM competences often focus on organizations as the unit of analysis. For example, studies on maturity models concentrate on organizational BPM capabilities (e.g., Van Looy et al. 2013), examining what competences should be improved or added to a project or a company in order to advance BPM effectiveness and efficiency. There is, however, a call for more attention and research on individual BPM competences (Gartner 2014b; Müller et al. 2014). Until now, there have been only a few studies focusing on the required and offered individual competences for conducting successful BPM initiatives. Some exceptions are outlined below.

Launonen and Kess (2002) analyzed 39 teams working in the field of Business Process Re-Engineering (BPR), mapping eight different categories of functional competences (innovation, teamwork, project work, etc.) as they relate to eight roles (innovator, organizer, chair, etc.). They found out that each of the roles expects a different competence composition.

Müller et al. (2014) analyzed BPM competences demanded by organizations. In order to determine competence requirements in typical BPM jobs, the study examined data from an online job platform and applied an established competence classification framework proposed by Todd et al. (1995). The study identified various typical combinations of competences required in the BPM field, called "ideal types". The demanded competences covered all areas of the Todd et al. (1995) framework: *technical* competences that comprise hardware and software competences; *business* competences that encompass domain, management, and social competences; as well as *systems* competences that consist of problem solving and development competences. Different BPM jobs required these technical, business, and systems competences in different proportions (in line with the results of Launonen and Kess 2002).

Antonucci and Goeke (2011) used questionnaires to identify the *responsibilities* of the four types of employees in the BPM field. In contrast to Müller et al. (2014), who described competences based on the nature of performed work (*horizontally*), Antonucci and Goeke (2011) reported on BPM positions based on their hierarchical levels (*vertically*). They identified such positions as "Business Process Analyst", "Business Process Architect", "Business Process Consultant", and "Business Process Director".

Finally, a recent study by Lohmann and Zur Muehlen (2015) identified five individual roles relevant for BPM. For each of these BPM roles, they compared the number of related positions offered on an online job advertisement portal with the number of LinkedIn users who state that they occupy these positions.

All of the aforementioned studies specified which individual competences are necessary for successful implementation of BPM projects and are demanded of BPM professionals. At the same time, a thorough investigation of the competences offered by BPM professionals is still missing in extant research (with the exception of the study of Lohmann and Zur Muehlen 2015). Gaining such insights though would further the understanding of the potential gap between BPM competence demand and supply, contributing to both BPM research and practice.

2.2 Theoretical Approaches to Gender and Technology

Gender is a multidimensional personality characteristic most commonly described by the masculinity-femininity continuum (e.g., Spence 1985). Gender is differentiated from one's biological male or female sex, meaning that women can score high on the masculinity scale and men can score high on femininity (West and Zimmerman 1987; Butler 1990; WHO 2013). Nevertheless, feminine attributes, which include *perceived feminine competences*, are still largely associated with women, while *perceived masculine competences* are typically associated with men (e.g., Cejka and Eagly 1999; Atwater et al. 2004; Joshi and Kuhn 2007). In other words, assumptions are made about female and male attributes. As Manstead et al. (1995) summarize: "Gender stereotypes are widely held beliefs about the characteristics and behavior of women and men" (p. 256).

Perceived feminine competences, which are required in technology-related fields, include, for instance, communication competences, customer and workplace relationship competences, and creativity (von Hellens et al. 2004; Trauth et al. 2012). Technical competences, such as programming or those related to system implementation or IT architecture, are perceived as being fundamentally entwined with masculinity (Henwood et al. 2000; Adam et al. 2006; Howcroft and Trauth 2008). As technology-related careers are perceived as more technical than creative (e.g., Clayton et al. 2012), and in most cultures it is still common to assign masculine attributes to men (e.g., Eagly et al. 2000; Wilson 2004), this perception of technical competences as being masculine reinforces gender stereotypes that IT jobs are more appropriate for men (Game and Pringle 1983; Mackinnon 1995; Craig 2015).

Both men and women might believe in gender stereotypes – that men are more interested in technology and women are not expected to, nor are they even capable of obtaining technical competences (e.g., Panteli et al. 1999; Robertson et al. 2001; Trauth et al. 2009). As a consequence, existing gender stereotypes about competences in technology-related professions are one of the reasons why women tend to find these professions undesirable and, therefore, do not persue them (e.g., Wajcman 1991; Robertson et al. 2001; Wilson 2004; Bayer Corporation 2010; Ashcraft et al. 2012; Trauth et al. 2012, 2015).

The underrepresentation of women in the IT field needs to be addressed not only due to the so-called *demographic argument* that the labor force in technology-related fields "cannot be satisfied by white men alone" (Trauth 2011, p. 562). Other reasons include the *innovation economy* argument that "brainpower and creativity fuel innovation, and the 'best brains' can come from a variety of bodies"; the *consumer argument* that "the varying needs of the entire consumer base [need to] be represented"; and the *equity argument* that "all people should have equal opportunities to pursue a career in IT" (Trauth 2011, pp. 561–562).

The three main theoretical approaches to studying the gender imbalance in technology-related fields include *gender essentialism*, *social construction of gender*, and *gender intersectionality* (e.g., Ridley and Young 2012; Craig 2015). The same approaches can be used to explain the differences in the ways men and women working in the IT industry present and apply their competences. Studies show that a horizontal segregation exists in the IT field, namely that women typically work "in what are considered to be 'softer' aspects of the profession" (Robertson et al. 2001, p. 112) – that is, in jobs where perceived feminine competences are mostly required (e.g., Adam et al. 2006). In this study we investigate whether the same phenomenon also holds true for the BPM field.

The *gender essentialism* viewpoint is that biological and psychological differences between men and women work to determine individual interests and, consequently, affect the competences obtained by an individual (e.g., Wilson 2004). In other words, according to this perspective, the competences men and women report and possess are a result of their innate abilities (Trauth et al. 2009). Although this approach has been criticised as untenable (Ridley and Young 2012), simplistic (Adya 2008), and reinforcing gender stereotypes (Howcroft and Trauth 2008; Quesenberry and Trauth 2012), it was applied in many studies. In studies favoring the essentialist perspective, the notions of gender and sex are considered synonymous, and sex is treated as one of the variables that fosters differences between men's and women's IT-related competences and behavior (e.g., Gefen and Straub 1997; Venkatesh and Morris 2000).

The *social construction of gender* perspective, in contrast, recognizes the roles of socialization, as well as cultural patterns and biases, in creating gender differences, so that these differences are a matter of culture, rather than nature (e.g., Harding 1987; Wilson 2004; Adya and Kaiser 2005). Thus, differences in self-reported competences in the technology-related professions can be explained by social expectations, which form gender stereotypes (Ahuja 2002). This might lead to a phenomenon of conformance of men and women to the socially *prescribed* behavior, resulting in, for instance, unconsciously presenting those competences in resumes, which are consistent with gender stereotypes (Wilson 2004; Trauth et al. 2012, 2015). In the social sciences, a social, rather than biological, explanation of gender differences has received wider acceptance (e.g., Light 2007; Ridley and Young 2012). Several studies claim that these social conventions are open to change since they are constructed by society, which is dynamic (Howcroft and Trauth 2008; Bassot 2012).

However, the social construction of gender approach has been criticised for treating women and men as homogeneous groups and generalizing about the experiences of all women and all men (Wilson 2004; Ridley and Young 2012). Therefore, an alternative *gender intersectionality* approach was proposed, which suggests that, for example, perceived masculine and feminine competences in the technology-related professions are formed not only by gender group-level influences but also by within-gender variation (Craig 2015). The related Individual Differences Theory of Gender and IT (IDT, Trauth 2002) identifies the reasons for the underrepresentation of women in the IT field, but can be also applied to explain the factors influencing the formation of gender stereotypes about the competences in technology-related professions. IDT considers three groups of significant factors: environmental influences, individual influences, and individual identity. Environmental influences also form the core of the preceding social shaping of gender perspective. Individual influences include factors such as personality traits or the influence of mentors and role models. Individual identity considers, among others, personal demographics factors such as age, ethnicity, or socio-economic class (Quesenberry and Trauth 2012).

We consider *social construction of gender* to be the most suitable lens for this study and follow this perspective in discussion and interpretation of the study findings. On the one hand, we agree with the critique of the *gender essentialism* perspective. On the other hand, the LinkedIn profiles collected in this study do not contain information about personality traits, role models, socio-economic class, etc., which makes an analysis of within-gender variation among BPM professionals not feasible at this stage and, thus, potentially subject to future research.

3 Method

In order to understand which competences are supplied by male and female professionals in the BPM field, we examined profiles from the LinkedIn professional online social network. In this section, we first justify the applicability of LinkedIn profiles as a source of data for our study. We then describe how the profiles were selected and how the relevant information was collected, cleaned, and normalized. Finally, we introduce the LSA text mining technique, and explain how we applied it for analyzing the supplied BPM competences.

3.1 Professional Online Profiles as a Data Source

Professional online social networks represent *social media business networks* that are used by individuals to gain and maintain contacts with other professionals (Aichner and Jacob 2015). LinkedIn has been identified as "the world's largest professional online social network" (Bastian et al. 2014, p. 1) with currently more than 380 million members worldwide (LinkedIn Corporation 2015). Professional online social networks in general, and LinkedIn in particular, bring professionals together by offering a platform where they can find jobs, projects, and colleagues based on competences and experiences. As Aichner and Jacob (2015) articulate, "when it comes to recruitment and headhunting, business networks are the most important source for companies" (pp. 261–262). Therefore, professional online social networks can be seen to contribute significantly to an individual's career progress. Particularly, the competences displayed on professional online profiles play an important role in individual career advancement and are, thus, a highly relevant object of study.

Beyond competences, a profile published on LinkedIn typically contains information about current and previous positions, education, interests, etc. It has, therefore, a similar content to a traditional Curriculum Vitae (CV), which is a privately created document that professionals use for application to a particular position. Several earlier studies refer to the great potential of CVs as a source of data for understanding a broad variety of workforce-related issues (Cañibano et al. 2008; Sandström 2009). However, obtaining a large number of traditional CVs is usually not feasible, as they are not publically available and people are typically reluctant to share them. At the same time, public profiles created by members of professional online social networks are easy to access, allowing for the collection of large volumes of data. Moreover, online platforms offer additional features to users, like connections to other users or endorsements for competences, which provide even more detailed information about individuals than traditional CVs. Finally, online profiles support the research process by allowing for structured searches, enhancing the identification of relevant profiles.

Online profiles published on social networking websites have already been used in earlier studies on professional competences. In the aforementioned study by Lohmann and zur Muehlen (2015), BPM-related job positions reported in LinkedIn profiles were analyzed and then compared with the demanded ones. Similarly, Chelaru et al. (2014) analyzed profiles extracted from About.me, LinkedIn, Twitter, and Facebook to understand how competences presented in social networks can be categorized into professions.

Against this background, we believe that profiles from professional online social networks are a valid data source for research purposes in general, and for our study in particular. In addition to the high number of users, there are two other reasons for choosing the LinkedIn platform for collecting information about the competences supplied by BPM professionals. First, LinkedIn members can tag their areas of expertise by selecting them from a list of existing competences or manually adding new ones (Bastian et al. 2014), and the built-in LinkedIn search engine allows for a search of people who mention specific terms in their profiles. Second, each profile contains a member's first and last name and usually also a picture, which provides the opportunity to identify the gender of selected members in order to analyze the sample gender distribution.

3.2 Data Collection

We collected LinkedIn profiles containing the term "business process" in autumn 2014. In order to be able to collect a higher number of profiles, we used a paid premium account, which allows for returning up to 500 hits per search query. Applying the following four search filters gave us an opportunity to, on the one hand, increase the number of profiles we could collect and, on the other hand, control for factors such as personal connections, country, industry, and company.

1. The functionality of the LinkedIn social network allows members to connect with each other, building sub-communities of *friends-of-a-friend*. In order to reduce the personal bias to the profiles displayed, those from the 1st and 2nd circles of connections (direct contacts and contacts of contacts) were excluded from the search and only the profiles from the 3rd circle of connections and everyone else ("3rd + Everyone Else" filtering option in LinkedIn) were included.
2. The profiles were searched in developed English-speaking countries, namely: the United States (USA), Canada, the United Kingdom (UK), and Australia. Such a choice was supported, first of all, by a high

number of profiles in them. Moreover, these countries are widely geographically distributed, but, at the same time, represent comparable *Western* cultures, controlling for potential cultural biases.

3. The next filtering criteria was *industry* (during registration all LinkedIn members need to enter an industry attribute, characterizing their current occupation). We chose the following three industries as they included the largest total number of relevant BPM-related profiles in the four countries mentioned above: Computer Software, IT, and Management Consulting. The IT focus of two out of three industries, which returned the largest number of profiles containing the term "business process", acts as a first indicator that IT still plays a key role in driving BPM in practice.
4. In order to further increase the number of profiles and to gain an opportunity to compare the current positions reported in them, the four companies (current employers) with the largest total number of relevant profiles in the considered four countries were chosen. The same companies were also on top of the lists of returned profiles for each of the three selected industries. All selected companies have between 200,000 and 380,000 employees and are active in the fields of IT and consulting, although they have different focuses: The first company is one of the "Big Four" auditing firms. The second is one of the world leaders in IT consulting. The third company is a global IT hardware, software, and service provider to consumers and businesses, as well as to public bodies. The fourth is also a multinational technology and consulting corporation. Three of the companies are headquartered in the USA while one is based in Europe.

The combination of these filters theoretically gives the opportunity to access up to 24,000 distinct profiles satisfying the search criteria (4 countries $\times$ 3 industries $\times$ 4 companies $\times$ 500 available profiles in each search iteration = 24,000). However, many combinations of filters returned less than 500 hits. As a result, 14,923 profiles were collected for further analysis.

The following semi-structured data was automatically extracted from the profiles: full name, current and past jobs, number of LinkedIn peer connections, competences, and number of endorsements for each competence. For each profile, we could also identify the first year of employment and, for the majority of profiles, also the first month of employment (if not, we assumed it to be January). Based on this information, we calculated the total work experience in months (up to November 2014).

In order to identify the gender of the selected members in an automatic way, the GendRE Application Programming Interface (GendRE API) of the NamSor web service (NamSor 2014) was used. GendRE API applies an onomastics approach (Carsenat 2013), returning, based on a first- and last name, a suggested gender and a level of certainty. The level of certainty can range from -1 to 1, with -1 meaning a male name with a 100 % certainty and 1 meaning a female name with a 100 % certainty.

3.3 Data Cleansing

Once the information was extracted, we cleansed it. Several cases had identical names and, therefore, were manually checked for duplicates. The majority of such cases, though, were related to different people bearing the same names. Seven profiles turned out to be duplicates, so the extracted information for them was manually checked and, where necessary, merged, creating one complete profile containing all the information.

For cases with unknown or uncertain (below 50 % certainty) gender, the data was manually screened, making decisions on the gender, or removing them. The profiles usually contained pictures, which made the gender identification for them straightforward. For each doubtful profile without a picture a search by first and last name using the Google web engine was performed. It was often possible to unambiguously identify gender based on the delivered pictures or by finding relevant profiles in other social networks (such as Facebook). For 39 cases, it was still not possible to identify the member's gender and, therefore, these cases were removed from further analysis. This number also includes profiles with evident fake names (e.g., "Hippie Chick").

As a next step, in order to gain a comprehensive picture of the competences offered by BPM professionals, we removed 4377 profiles, in which the search term "business process" did not appear as one of the areas of expertise, but was contained only in other profile sections like, for instance, in comments of colleagues.

Finally, we removed 95 cases with missing information about entry dates to previous and current jobs, as it was not possible to calculate the total months of experience for them.

All numerical fields were also checked for outliers. Several cases contained positions dating back to the year 1900, which were considered typing errors and, therefore, were deleted without removing the entire case. No further anomalies in the data were revealed. The resulting study sample contained 10,405 cases that provided sufficient data for the analysis of competences supplied by male and female BPM professionals.

3.4 Categorization of Positions

Beyond the competences offered by male and female BPM professionals, we also obtained information about people's current positions. Although the related studies discussed above attempted to specify BPM positions, there is still a lack of established and commonly accepted wording for BPM job titles (Kokkonen 2014). This makes it difficult to compare current positions *horizontally* (i.e., based on the nature of performed work). Therefore, we decided to instead perform a *vertical* analysis of current positions based on their hierarchical levels.

9622 cases out of 10,405 provided details on current employment. Within these profiles, we could initially identify 5244 distinct positions. This number could be reduced to 5189 by harmonising specific terms in job titles (e.g., "Snr." or "Sr." were replaced by "Senior") and company-specific abbreviations (e.g., "AM" was substituted with "Associate Manager"). We then further *normalized* positions by reducing them to their *core* (e.g., "*Company name* Senior Consultant, EMEA" was normalized to "Senior Consultant"). The normalized positions contained combinations of 76 distinct terms, which were revealed as occurring most frequently in job titles. These terms describe seniority levels (e.g., "Senior", "Lead", "Head of", "Assistant"); nature of occupation (e.g., "Architect", "Consultant", "Accountant"); or special roles (e.g., "Vice President", "Principal", "Partner"). In total, we were able to reduce 5189 distinct positions to 598 distinct normalized positions.

Two researchers then independently categorized the normalized positions into the following position levels: *non-managerial personnel or interns* (Position Level 1); *line or middle managers* (Position Level 2); and *upper or top managers* (Position Level 3). Online career portals, job portals, and forums discussing hierarchical levels of positions in the selected companies helped to identify hierarchical structures and assign positions to these three levels.

Cases for which the codification was ambiguous were discussed and resolved involving a third researcher. 373 profiles where none of the terms characterising a hierarchical level of the current position could be found (e.g., "Customer Focused Digital Transformation") were excluded from the further analysis of positions.

Assigned position levels were controlled against work experience calculated for each profile. We identified 98 abnormal profiles assigned to Position Level 3 with less than 5 years of work experience. We randomly checked several of these profiles and found that most of them had been created very recently. We assume that these profiles were not yet fully completed and included only information about current or most recent positions, not providing a complete career history. These incomplete profiles were excluded from the further analysis of current positions so that the final sample included 9151 profiles (or 87.9 % of all cases).

3.5 Latent Semantic Analysis of Competences

In social science research, the analysis of unstructured textual documents, like CVs, has traditionally been done manually through coding, which made the process costly and subject to many limitations and biases (Quinn et al. 2010). Computer-aided qualitative data analysis (CAQDA) software, such as NVivo or Atlas.ti, can support and accelerate the manual coding process to a certain extent, for example, by automatically searching for further instances of already coded phrases, but does not allow to automatically discover recurring patterns in texts. Hence, we turned to unsupervised machine learning algorithms for inductively categorizing text documents. This class of text mining methods can infer categorizations of documents from a corpus in a data-driven way, necessitating neither manual coding nor the existence of predefined categorisation schemes.

In particular, we used latent semantic analysis (LSA), a topic modeling technique that has received growing attention from Information Systems researchers over the last years (e.g., Evangelopoulos et al. 2012). LSA has been used in Information Systems research, for example, for the automated analysis of research articles (Larsen et al. 2008; Sidorova et al. 2008; Indulska et al. 2012); corporate reports (Reuter et al. 2014); social media communications (Evangelopoulos and Visinescu 2012); and job advertisements (Müller et al. 2014).

It is based on the "distributional hypothesis" of statistical semantics (Sahlgren 2008): words that co-occur together in similar contexts tend to have similar meanings (Turney and Pantel 2010). Consequently, words that co-occur frequently in similar contexts (e.g., "process", "map", "draw", "model", "BPMN") can be interpreted as topics (e.g., "process modeling") and can be used to categorize documents accordingly. In order to identify such word patterns (or topics) in a large collection of documents, LSA performs a dimensionality reduction technique called Singular Value Decomposition (SVD) on a term-document matrix. A term-document matrix is a matrix representation of a document collection that contains one column for each document in the collection and one row for each word appearing in these documents; the cells of the matrix contain the number of times a term appears in a document (Manning et al. 2008). Similar to factor analysis or principal component analysis, the SVD reduces the dimensionality of the term-document matrix. The results are so-called latent semantic factors, each linked to high-loading words and high-loading documents. Together, these high-loading words and high-loading documents can be interpreted as topics – that is, word patterns that repeatedly occur in specific documents.

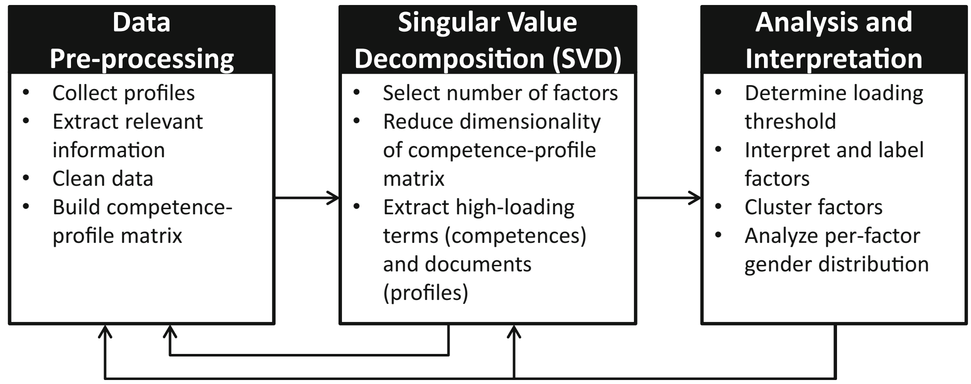

Fig. 1 The process of LSA (adapted from Evangelopoulos et al. 2012)

In our case, we applied LSA to the competence section of the collected LinkedIn profiles. Hence, the first step included pre-processing the profiles to build a competence-profile matrix containing the number of times each competence appeared in each profile (cf. Fig. 1). We could identify 3998 distinct competences in 10,405 collected profiles.

In the second step, we followed the generic LSA process outlined by Evangelopoulos et al. (2012) and performed the SVD on the competence-profile matrix using the statistical computing software R. This requires defining the number of factors (topics) to be extracted. So far, no standard procedures for determining an appropriate number of factors exist. Rather, the researcher is advised to manually explore alternative numbers of factors and qualitatively assess the results (Evangelopoulos et al. 2012). After exploring 10-, 12-, 15-, 20-, 25-, and 30-factor solutions, we decided to select 12 factors for further interpretation, as the solutions with higher number factors contained more and more near duplicates (very similar factors).

In the third step, the extracted high-loading competences (cf. Appendix A; available online via http://link.springer.com) and high-loading profiles were analyzed and interpreted. Therefore, a loading threshold had to be selected which defined how many terms and documents should be regarded as relevant for each factor. Based on the approach proposed by Sidorova et al. (2008), a loading threshold of top − (1/k × 100) % was determined, where k is the number of factors. As a 12-factor solution was selected for this study (k = 12), 8.3 % of high-loading terms and profiles were derived for further analysis. The resulting list of the top 333 extracted competences for each factor (8.3 % of total 3998 competences) was independently analyzed by four researchers. Each researcher had to screen them, suggesting the most representative label for each factor. The labels provided by each researcher were then compared, showing an immediate agreement on labelling of 10 out of 12 factors. Labelling of the other two factors was determined during a discussion involving all researchers. The resulting 12 categories of competences are clearly distinguishable and are presented in the following section.

4 Results

This section presents the results of the profile analysis. In particular, the profiles of male and female BPM professionals are compared based on reported competences, specified current positions, as well as numbers of connections, endorsements, and months of experience.

4.1 Categories of Competences Supplied by Business Process Management Professionals

Interpretation of the 12-factor solution generated by applying LSA resulted in the following 12 clearly distinct categories of competences supplied by BPM professionals (see Appendix A for a summary of high-loading competences):

1. *Strategic Management* The typical competences forming this category are related to higher management qualifications, such as Business Transformation, Requirements Analysis, Change Management, IT Strategy, and Program Management.
2. (*IT*) *Project Management* The competences comprising this category include those required to run projects either inside a company or as an external consultant (e.g., ITIL – Information Technology Infrastructure Library); gained certificates (e.g., PMP – Project Management Professional); or work experience in such specialised groups as PMO (Project Management Office). Further examples of high-loading competences include Project Delivery, Stakeholder Management, and Project Portfolio Management.
3. *Enterprise Architecture*,
4. *ERP* (*Enterprise Resource Planning*) *Solution Architecture* (*SAP*), and

5. *ERP Solution Architecture* (*Oracle*) These technical categories focus on either general enterprise architecture or more specific knowledge of such systems as SAP and Oracle. Category [3] has a stronger managerial focus than the other two, and is represented by such competences as Service-Oriented Architecture (SOA), Enterprise Software, or Technical/Application Architecture. Further examples of high-loading competences include Business Process Design, Organizational Design, Enterprise Architecture, and EAI (Enterprise Application Integration). High-loading competences for Category [4] include SAP R/3, SAP Implementation, and other ERP-related competences like Advanced Business Application Programming (ABAP), SAP NetWeaver, SAP Business Information Warehouse (BW), SAP for Order-to-Cash, or SAP for Retail. Category [5] consists of competences related to Oracle solutions, such as Oracle e-Business Suite, Oracle HR (Human Resources), or Oracle Applications.
6. *Software Development* The category contains technical competences required to conduct software development projects, such as those related to certain programming languages (e.g., Java, Visual Basic, or Java Server Pages – JSP), as well as to procedure models, like Scrum or Waterfall, or server platforms. Further examples of high-loading competences include Systems Development Life Cycle (SDLC), Requirements Gathering, Software Project Management, Solution Architecture, and Agile Methodologies.
7. *IT Service Outsourcing* The competences relevant for this category are related to either offering a cloud solution or outsourcing a company's own IT landscape, such as Service Delivery, Outsourcing, IT Service Management, IT Outsourcing, and Software as a Service (SaaS).
8. *Business Intelligence* The competences making up this category are related to different aspects of storing, maintaining, and analyzing corporate data. They include such technical and software-related competences as Structured Query Language (SQL) or Cognos, as well as conceptual competences (e.g., data modeling or data warehouse architecture). Further examples of high-loading competences include Data Analysis, Data Warehousing, Extract, Transform and Load (ETL), Master Data Management, and Business Objects.
9. *Auditing and Risk Management* The competences of this category cover various types of auditing (internal, IT, financial), as well as knowledge about standards like USA GAAP (United States of America General Accepted Accounting Principles) or ISO 27001 (International Organization for Standardization) and governance mechanisms (e.g., Sarbanes–Oxley Act). Furthermore, the category includes such risk management competences as security and disaster recovery. Examples of high-loading competences include Internal Controls, Internal Audit, Enterprise Risk Management, IT Audit, and Risk Management.
10. *Accounting and Finance* The category comprises finance-related competences at managerial (e.g., Corporate Finance, Financial Accounting); conceptual (e.g., Financial Modeling); or operative (e.g., Forecasting, Financial Analysis, Reporting) levels. Further examples of high-loading competences include Financial Modeling, Financial Analysis, Financial Reporting, Corporate Finance, and Managerial Finance.
11. *Supply Chain Management* (*SCM*) The category covers supply chain-related competences on the source side (e.g., Purchasing, Procurement, Global or Strategic Sourcing, or Supplier Development); the production side (e.g., Inventory Management, [Lean] Manufacturing, or Material Management); or the management side (e.g., Six Sigma, Supply Chain Optimisation, or Process Improvement). Further examples of high-loading competences include Supply Chain Management, Supply Chain, and Logistics.
12. *Human Resource* (*HR*) *Management* The competences of this category deal with the organization of corporate human resources (human capital). Most of them are related to management (e.g., Talent Management, Personnel Management, Performance Management, and Organizational Design). Some also focus on operative HR tasks (e.g., Training, Recruiting, SAP HR), as well as changes in corporate culture (e.g., HR Transformation, Employee Engagement, or Culture Change).

The identified categories of competences suggested that sub-groups of similar competences exist, as the researchers either assigned similar labels to multiple factors, or the high-loading terms of factors partially overlapped. Hence, we decided to try to cluster the factors based on their term loadings. We applied hierarchical clustering with Pearson's correlation coefficient as the distance measure and single linkage as the agglomeration method. The resulting dendrogram depicting the similarities between competence categories is presented below (Fig. 2). The dendrogram is read from bottom to top: the earlier two leaves are joined in the 'tree', the more similar they are. For example, the competence categories Strategic Management (Category [1]) and HR Management (Category [12]) are very similar

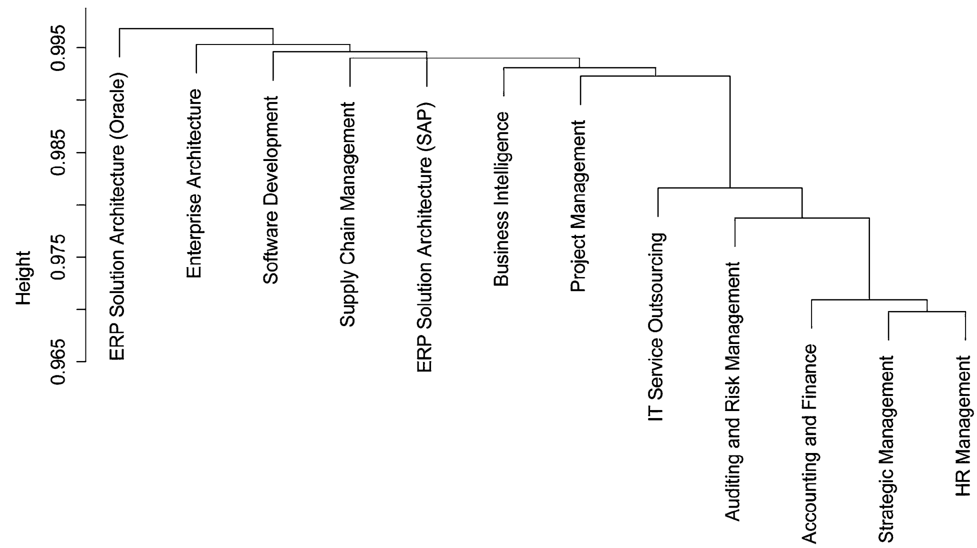

Fig. 2 Dendrogram representing the similarities between the competence categories

to each other, in terms of the vocabulary used to describe specific competences in these areas. Overall, the dendrogram reveals a dichotomy between domain-specific/management related competence categories (right part of the 'tree') and technical competences (left part of the 'tree'). Yet, it also shows that the vocabulary used to describe management competences is more homogeneous than the vocabulary of the more technical competences, which can be explained by the distinct technical terms (e.g., ERP, SQL) and vendor/product names (e.g., SAP, Oracle) used to describe IT competences.

Overall, the identified competence categories represent the variety and heterogeneity of the BPM field, ranging from technical competences to managerial and domain competences. At the same time, a deeper analysis of competences in each category reveals that the holistic nature of BPM (cf. vom Brocke and Rosemann 2015) is not completely reflected in our dataset, particularly since a domination of technical categories can be observed (Categories [3]–[7]).

4.2 Gender Distribution in the Study Sample

Table 1 summarizes descriptive statistics of the final study sample, including the male/female ratio in the countries and industries under investigation. Overall, the majority of the selected profiles are from the IT industry (49.3 %) and the USA (35.5 % of the overall sample). The second finding is in line with the overall statistics of LinkedIn users in the four selected countries (Statista 2015).

Female profiles comprise only 28 % of the study sample, which shows a clear male domination. It does need to be mentioned, however, that there are more men among LinkedIn members, with the following shares of women in the selected countries (number was derived by the Quantcast portal – http://www.quantcast.com): 40 % in the USA (vs. 27.1 % in our sample); 36 % in Canada (vs. 30.4 % in our sample); 35 % in the UK (vs. 25.9 % in our sample); and 29 % in Australia (vs. 29.7 % in our sample). In our sample, thus, the largest share of women is in the profiles from Canada, followed by those in Australia, USA, and UK. It is surprising that for Australia the share of women in our sample is above the country average, whereas in all the other countries it is below the average. Nevertheless, based on a one-sample t test, the share of women in our study sample (28 %) is significantly lower (at the 0.001 level) than the average share of women on LinkedIn in the four analyzed countries (35 %).

Hence, we can conclude that in our dataset of BPM professionals, women are underrepresented. This result can be explained by the domination of profiles from the IT industry (49.3 % of the overall sample), where, as it was discussed earlier, the share of women is generally low (e.g., U.S. Bureau of Labor Statistics 2013). As for the gender distribution across industries, the largest share of women is in the Management Consulting industry (30.4 %), followed by IT (27.3 %), and Computer Software (25.4 %). These differences in the shares of women between the three industries are statistically significant at the 0.01 level, but the effect sizes are negligible.

4.3 Gender Distribution at Different Position Levels

Chi squared tests with Cramer's V (φ_c) were performed to measure the association between gender and position level (Cramér 1946). The results show that on each higher career level the share of women drops (Table 2): 31.3 % at the non-managerial personnel level (Position Level 1); 28.2 % at line/middle management (Position Level 2); and 22.5 % at the upper/top management positions (Position Level 3).

Table 1 Study sample and its gender distribution

Country	Industry	Men		Women		Total	% of the whole sample (%)
		N	%	*N*	%		
United Kingdom	Computer Software	268	82.0 %	59	18.0	327	3.1
	IT	895	76.1	281	23.9	1176	11.3
	Management Consulting	735	69.3	325	30.7	1060	10.2
Total United Kingdom		1898	74.1	665	25.9	2563	24.6
United States	Computer Software	798	72.5	303	27.5	1101	10.6
	IT	1066	74.6	363	25.4	1429	13.7
	Management Consulting	830	71.1	337	28.9	1167	11.2
Total United States		2694	72.9	1003	27.1	3697	35.5
Australia	Computer Software	116	75.8	37	24.2	153	1.5
	IT	910	70.8	376	29.2	1286	12.4
	Management Consulting	506	68.3	235	31.7	741	7.1
Total Australia		1532	70.3	648	29.7	2180	21.0
Canada	Computer Software	143	73.3 %	52	26.7	195	1.9
	IT	862	69.3	381	30.7	1243	11.9
	Management Consulting	362	68.7	165	31.3	527	5.1
Total Canada		1367	69.6	598	30.4	1965	18.9
Total Computer Software		1325	74.6	451	25.4	1776	17.1
Total IT		3733	72.7	1401	27.3	5134	49.3
Total Management Consulting		2433	69.6	1062	30.4	3495	33.6
Total		7491	72.0	2914	28.0	10,405	100

Table 2 Categories of competences supplied by BPM professionals (12-factor solution)

Nr.	Category of competences	Deviations in the shares of women in high-loading profiles from the overall study sample			
		Overall share of women (28 %)	Share of women at each position level		
			Non-managerial (31.3 %)	Line/middle management (28.2 %)	Upper/top management (22.5 %)
[1]	Strategic Management	−1.8	−3.9	+1.6	−3.3
[2]	(IT) Project Management	+1.4	−3.3	+5.2*	+1.6
[3]	Enterprise Architecture	−4.8**	−9.8***	−4.8	+2.7
[4]	ERP Solution Architecture (SAP)	−6.0***	−7.8**	−4.7*	−1.1
[5]	ERP Solution Architecture (Oracle)	−3.7*	−1.9	−4.9*	−0.4
[6]	Software Development	−8.3***	−7.0**	−14.2***	−12.5**
[7]	IT Service Outsourcing	−3.4*	−9.8*	+0.7	−8.1**
[8]	Business Intelligence	−1.9	+2.5	−6.9*	−8.1**
[9]	Auditing and Risk Management	−2.7	−5.3	+0.9	−6.5*
[10]	Accounting and Finance	−3.2*	−1.0	−4.9*	−5.3
[11]	Supply Chain Management	−5.5***	−7.3**	−5.6*	−1.4
[12]	HR Management	+11.4***	+3.2	+12.5***	+18.8***

* Significance at the 0.05 level

** Significance at the 0.01 level

*** Significance at the 0.001 level

This drop is significant at the 0.01 level, although the effect size is negligible ($\varphi_c = 0.074$). Overall, the majority of both male (41.9 %) and female (42.6 %) BPM professionals occupy line/middle managerial positions. Only 19.6 % of all women are on upper/top managerial positions, versus 26 % of all men.

Furthermore, it is interesting that at the *organizational entry* career stage (less than 1.5 years of work experience) there are equal shares of men and women (50 %) who all are at the non-managerial positions. All of the early career employees (from 1.5 to 5 years of work experience) are also at the Position Level 1, but here the share of women is already lower (38.1 %). Among employees who are at their mid-careers (from five to 15 years of work experience), women continue to be underrepresented: they occupy 31.6 % of non-managerial positions, 29.5 % of line or middle management positions, and 24.6 % of upper or top management positions. The share of women at each position level is even lower, when analyzing the employees with more than 15 years of work experience: 27.7 % at Position Level 1, 27.1 % at Position Level 2, and 21.6 % at Position Level 3.

It is notable that when having a look at the upper and top management positions alone, the share of women among employees at mid-careers is higher than among those at later careers (24.6 vs. 21.6 %). One explanation could be that women drop out from the workforce at a later career stage due to child rearing. However, such a positive shift in the share of younger female top managers (we assume that work experience is highly correlated with age) might also be the sign of a trend that it becomes more possible for women to gain a managerial position.

We also analyzed the terms that appeared most often in current positions (cf. the “Method” section for the identified 76 distinct terms), comparing their frequencies of occurrence in the profiles of men and women. We found statistically significant differences between the profiles of men and women (compared to the overall sample) in the occurrence of several terms: those signifying top managerial positions (“Senior”, “Vice President”, “Partner”, “Managing”, “Executive”, and “Director”) or technical positions (“Architect”) occur relatively more often in male profiles. On the other hand, terms characterizing line/middle managerial positions (“Project”, “Program”, and “Manager”) or non-managerial and non-technical positions (“Analyst”, “Assistant”, “Coordinator”) occur relatively more often in female profiles.

4.4 Gender Distribution across Categories of Competences

As a next step of our analysis, we had a look at high-loading profiles, i.e. the profiles that best represent each of the twelve categories of competences supplied by BPM professionals. Applying the aforementioned loading threshold of top $-$ (1/k $\times$ 100) %, proposed by Sidorova et al. (2008), where k is the number of factors (k = 12 in the current study), we investigated the top 867 profiles of each factor (8.3 % of total 10,405 profiles).

We compared the gender distribution in high-loading profiles with the overall study sample (Table 2). For that, a series of t-statistics tests were performed. First, the share of women among high-loading profiles forming each factor was compared to the share of women in the overall study sample (28 %). Second, the shares of women at each position level within each category of competences were compared to the respective shares of women in the overall study sample who are at non-managerial positions (31.3 %), line/middle management (28.2 %), and upper/top management (22.5 %).

For eight (out of twelve) factors the difference in gender distribution turned out to be statistically significant: in seven categories of competences (Enterprise Architecture, ERP Solution Architecture (SAP), ERP Solution Architecture (Oracle), Software Development, IT Service Outsourcing, Accounting and Finance, and Supply Chain Management) there are *significantly more men* than in the overall sample. The only competence category in which the *higher share of women* (compared to the overall sample) is statistically significant, is HR Management. This may be explained by the rather non-technical nature of HR, compared to the other categories, thus, signaling a possible existence of gender stereotypes in the BPM field. Together with (IT) Project Management, these are the only categories with: (a) higher shares of women than in the overall study sample, containing 29.4 and 39.4 % of women respectively; as well as (b) statistically significant higher shares of women at managerial positions, compared to the overall study sample. These two categories are also very similar to each other in terms of the vocabulary used to describe competences in these areas (Fig. 2). For the other ten categories, the share of women among high-loading profiles is lower than in the overall study sample. For most of the categories with the higher share of men (except for Enterprise Architecture), a statistically significant underrepresentation of women in managerial positions (Position Levels 2 and/or 3) was also revealed. The lowest overall share of women, as well as at managerial positions, is observed in the Software Development category, which can be considered the most technical area, again indicating the potential existence of gender stereotypes at work.

4.5 Gender Differences in Professional Online Profiles

To gain a deeper understanding of gender differences in the online profiles of BPM professionals, we analyzed the

Table 3 Significance and effect sizes of relationships between variables in the study sample

	Mean value		Eta Squared	Pearson's (r)		
	Men	Women		Sum of endorsements	Number of connections	Months of experience
Number of competences	25.98	22.77	0.013**	0.645**	0.382**	0.238**
Sum of endorsements	163.57	127.07	0.012**		0.546**	0.323**
Number of connections	341.14	298.43	0.016**			0.128**
Months of experience	200.88	183.62	0.006**			

** Significance at the 0.01 level

following information extracted from each of the profiles: numbers of competences and connections, sums of endorsements, and months of experience (all coded as interval variables). In order to get a more profound understanding of the study sample, we explored the significance and effect sizes of the associations between gender and each of these interval variables. The associations were tested by a series of independent samples t tests with Eta Squared (η^2) (Pierce et al. 2004). Here we assumed the gender variable to be independent and the interval variables to be dependent. The outcomes of independent samples *t* tests revealed that in our sample women, on average, tag fewer competences than men, and have lower numbers of endorsements, connections, and months of experience (Table 3). All these differences are statistically significant at the 0.01 level.

The fact that female BPM professionals, on average, tag fewer competences in their profiles than males does not necessarily imply that they have less expertise, but rather could indicate that they are more likely than men to be conservative in how they describe what they can do. Such reasoning is in line with previous research following the *social construction of gender* perspective. Studies show that women are more likely to understate their competences and have lower confidence and degrees of self-efficacy in comparison to men. (Wilson 2004; Institute of Management and Leadership 2011; Sandberg 2013; Litzler et al. 2014; Sturm et al. 2014).

The lower average sum of endorsements is a consequence thereof: here Pearson's *r* correlation coefficient (e.g., Pearson and Galton 2012) shows that the number of competences is highly correlated with the sum of endorsements (Table 3). Having fewer connections might be another reason why women have fewer endorsements than men, as often LinkedIn members are asked to endorse those they are connected to, so the more connections one has, the more endorsements he/she is likely to get. The latter argument is supported by Pearson's *r* correlation coefficient between these interval variables (Table 3).

One possible explanation as to why women in our sample have on average fewer connections than men, could be the so-called 'old boys' network' phenomenon, which is common in technology-related fields and has been reported in earlier studies (e.g., Loiacono et al. 2013; Trauth 2013). The idea is that people working in the IT field, mostly men, tend to build professional connections with those similar to them, i.e. other men, and thus exclude women.

The finding that women, generally, have fewer months of experience can be explained by their "interrupted pattern of employment", which is also one of the reasons for their limited opportunities in the labor market (Panteli 2012, p. 392). In other words, women, who traditionally take (longer) parental leave, are out of the workforce for a longer time than men.

5 Discussion

In this section, we discuss the nature of BPM-related competences and the differences in their presentation by male and female professionals, which indicate the potential existence of gender stereotyping occurring in the field. Moreover, we provide recommendations for addressing the revealed underrepresentation of women among BPM professionals, which can contribute to closing the BPM competence gap.

5.1 The Nature of the Competences Supplied by Male and Female Business Process Management Professionals

In order to gain a more profound understanding of the nature of the competences at hand, we apply two established frameworks suitable to categorise BPM competences: (1) the BPM Maturity Model by Rosemann and vom Brocke (2015) that supports the holistic nature of BPM, and (2) the competence classification framework by Todd et al. (1995), which is renowned in the IT-related fields.

1. First, we map the twelve identified BPM competence categories to the six dimensions of the BPM Maturity Model: *strategic alignment*, *governance*, *methods*, *IT*, *people*, and *culture* (Rosemann and vom Brocke 2015). Each of these dimensions relates to one or more of the

identified competence categories. For example, Strategic Management [1] competences support capabilities in *strategic alignment*, Business Intelligence [8] and Auditing [9] competences foster *governance* capabilities, Project Management [2] competences offer specific *methodological* capabilities, Software Development [6] represents one of the *IT-related* competence areas, and HR Management [12] reflects competences in the areas of *people* and partially *culture*. Beyond covering specific facets of BPM in general, the identified categories also contain domain-specific knowledge areas such as Accounting and Finance [10], Supply Chain Management [11], and HR Management [12]. Although our results show a broad range of competences offered by BPM professionals, we, nevertheless, argue that the holistic nature of BPM is not fully reflected in our dataset. For example, the *culture* dimension is hardly covered through the supplied competences we identified. While one may argue that it is difficult to self-report competences related to *culture* in the area of BPM, research has identified specific cultural values that are important for the success of BPM initiatives, such as internal and external customer orientation and cross-functional teamwork (Schmiedel et al. 2013). Such qualities can be considered cultural competences in BPM, which, however, did not occur in the identified competence categories.

2. Second, we map the twelve identified categories to the framework by Todd et al. (1995), which distinguishes between *business*, *technical*, and *system* competences (cf. Sect. 2). Regarding *business* competences, we can observe a pervasiveness of *domain*-specific competences in such categories as IT Service Outsourcing [7], Accounting and Finance [10], Supply Chain Management [11], and HR Management [12]. *Management* competences are also widely represented in the Strategic Management [1], Project Management [2], and Auditing and Risk Management [9] categories. However, *social* competences do not seem to be supplied extensively. While such competences can be partially observed in the HR Management [12] category, we argue that this category refers predominantly to domain knowledge and that social competences in this case focus on inter-personal skills independent of a specific department.

As for *technical* competences, there are two comparable categories which focus on specific *software* competences, namely ERP Solution Architecture (SAP) [4] and ERP Solution Architecture (Oracle) [5]. However, non-ERP-related software competences, as well as any *hardware* competences, are not explicitly covered.

Regarding *systems* competences, *problem solving* competences are reflected only in the Business Intelligence [8] category and are, thus, not as prominent as *development* competences, which are dominant in the Enterprise Architecture [3] and Software Development [6] categories.

Thus, technical and system competences seem to be dominant among those supplied by BPM professionals. This fact shows that BPM is still very technical in practice today, although, Hammer (2015), for example, claims that IT is “at most a peripheral aspect of BPM” (p. 3). At the same time, social and analytical competences, as well as those related to special software or hardware are under-represented on the supply side. There may be two reasons for this: either such competences are indeed not present in the workforce, or employees do not explicitly mention them because they do not consider them essential to report.

While we generally identify a gap in self-reported competences on the *softer* aspects of BPM, such as cultural and social competences (which are stereotypically perceived as feminine), it is difficult to draw conclusions about an actual lack of these competences, since they are self-reported. However, the revealed focus on the presentation of technical competences (which are stereotypically perceived as masculine), supported by the fact that the majority of the returned profiles are related to the IT or Software development industries, indicates that BPM remains largely a technical field. There might be a lack of awareness among BPM professionals that social and cultural competences are also demanded by organizations (as indicated, for instance, in the study by Müller et al. 2014). Comparing the identified supplied BPM competence categories with the categories of demanded competences from the study of Müller et al. (2014), which likewise applied the Todd et al. (1995) framework, we can conclude that the supplied competences are not as diverse as the demanded ones. In other words, while organizations express needs for a very diverse set of BPM-related competences, employees report a far narrower variety of competences in their public profiles. Overall, the revealed twelve categories of competences supplied by BPM professionals show a domination of technical categories (Categories [3]–[7]).

As for gender distribution, all five IT-related categories are represented by mostly male profiles – the share of representative female profiles in each technical category is significantly lower than in the overall study sample (28 %). Moreover, for the most technical category, Software Development [6], we found the lowest share of women (19.7 %). On the other hand, the share of women reporting competences related to arguably the most non-technical category, HR Management [12], is significantly above average (39.4 %).

According to the *social construction of gender* theoretical approach, such self-presentation of competences on professional online social networks by both male and female BPM professionals might indicate that they are prone to gender stereotypes. Gender stereotyping in relation to competences means that technical competences are perceived as masculine and are associated with and presented by mostly men, while perceived feminine competences, such as those related to human capital, are associated with and more commonly presented by women (cf. Sect. 2). The social shaping of gender perspective acknowledges that the presentation of competences might be influenced by perceived social norms and expectations – that is, male professionals might feel expected to emphasize their technical expertise, while female professionals might tend to diminish their technical competences (*the impostor syndrome*), emphasizing instead their expertise in more feminine competences (Henwood et al. 2000; Wilson 2004). This proposition, however, requires further investigation and a collection of more detailed information about BPM professionals (e.g., through interviews).

5.2 Gender Imbalance in the Business Process Management Field

In addition to the revealed differences in the presentation of competences by male and female BPM professionals, the results show that women are underrepresented in the study sample. Although underrepresentation of women in technology-related fields has been extensively discussed in prior work, no specific statistics on the number and demographics of BPM professionals could be identified. Therefore, our study is the first one that provides empirical evidence that the BPM field is affected by gender imbalance, like other technology-related fields. Further, while the difference between the shares of women in our study sample (28 %) and across all LinkedIn users in the four countries under investigation (35 %) is not extremely high, it is still significant.

Further analysis of current positions reveals that the share of female BPM professionals decreases on each higher career level, with only 22.5 % of the upper/top management positions being occupied by women. Thus, women in BPM, just like women in IT (e.g., Trauth et al. 2009), seem to face the so-called ‘glass ceiling’, which is “an unacknowledged barrier to advancement in a profession, especially affecting women and members of minorities” (Oxford Dictionaries 2015).

We, thus, call to BPM researchers and practitioners to tackle the challenge of the existing gender imbalance in the field by researching and implementing new BPM interventions – specific activities aimed at changing the status quo (e.g., Craig 2015). Addressing the underrepresentation of women in BPM at all career levels could be a first step in reducing the lack of qualified professionals in the field. Balancing the gender ratio would also make BPM teams more diverse, which, on the one hand, would lead to “superior productivity and financial performance compared with homogeneous teams” (Barker et al. 2014, p. 2), and, on the other hand, benefit society more generally by raising equity in the opportunities men and women have in pursuing their careers (Trauth 2011).

We argue for implementing interventions aimed at enriching the BPM workforce by motivating more qualified women to enter it. In particular, we call for interventions aimed at fighting gender stereotypes about competences. The main idea behind such interventions is to tackle the unconscious bias that suggests women are not expected to possess perceived masculine competences. For instance, the emergence of more visible female role models who have technical competences could support the image that women are viable contributors in IT-related fields. Such interventions should be encouraged on a number of levels (with students and employees as target audiences). We also recommend implementing interventions that create and raise awareness about the wide range of career opportunities in BPM, not only those requiring technical competences. Studies indicate that a holistic set of competences, perceived as both masculine and feminine, are demanded in the BPM field (e.g., Müller et al. 2014), but are not yet sufficiently supplied.

Intervention programmes should also aim at increasing women’s self-efficacy and confidence, as gender stereotyping impacts such qualities and could, therefore, be valid reasoning for our finding that female BPM professionals tend to tag significantly fewer competences in their LinkedIn profiles than men. This argumentation is in line with prior studies following the *social construction of gender* perspective (e.g., Wilson 2004; Litzler et al. 2014; Sturm et al. 2014). In such intervention programs, women might be assisted in reconsidering the ways they describe their competences in CVs and professional online profiles.

6 Conclusion

The calls for more research on (1) human capital in BPM (Rosemann et al. 2006; Kokkonen 2014); (2) gender stereotypes in technology-related fields (Trauth et al. 2012, 2015); and (3) gender and technology in general (e.g., von Hellens et al. 2012) motivated us to investigate the role of gender in BPM competence supply. As very little is known about this research area and, in particular, as we observe a lack of theory addressing the shortage of professionals in the BPM field, we deemed it important to gain a deeper understanding of the phenomenon in an exploratory study. Therefore, we collected and analyzed a set of 10,405 LinkedIn profiles of BPM professionals, employing the

LSA text mining method. Against this background, our study not only contributes to the under-theorized field of BPM competence supply, but also presents a novel approach to exploratory research.

In our study, we identified twelve categories of competences supplied by BPM professionals and analyzed them applying the *social construction of gender* perspective. Our results show that BPM professionals tend to work in both technical (IT and Software Development) and managerial (Management Consulting) industries, although the self-reported competences are predominantly technical. Women tend to present more stereotypically feminine competences, while men advertised more stereotypically masculine ones. While the *essentialist approach* would refer this finding to biology and innate abilities, according to the *social construction of gender* perspective it appears that BPM professionals may be affected by gender stereotypes. Further investigation is needed though in order to make a conclusion about the exact reasons behind this phenomenon. For example, interviews with some of the people forming our dataset could enhance the understanding of the study findings. The data collected did not allow for an analysis of within-gender variation among BPM professionals and, thus, there is a need for further research on gender stereotypes and their relation to competences in the BPM field, by applying the *gender intersectionality* perspective.

From the mapping of the identified categories of supplied competences to the BPM Maturity Model by Rosemann and vom Brocke (2015), and the competence classification framework by Todd et al. (1995), it can be concluded that the offered categories, although quite diverse, do not fully represent the holistic nature of BPM. Specific gaps in self-reported competences include cultural and social competences, as well as analytical competences and those related to special software or hardware. These competences are relevant and demanded by organizations, but seem to be underrepresented on the supply side of the BPM job market. Future research can build on these findings, for example, by examining how far social and cultural competences are actually present in the BPM workforce, beyond what is reported in professional profiles, and analyzing how far such competences influence the process performance of organizations.

The study results also show that women are underrepresented among BPM professionals forming the study sample and that their share decreases on each next career level. These findings are in line with the state in other technology-related fields and can be extrapolated to the BPM workforce in the four countries under investigation. Although gender imbalance and vertical segregation in IT have been widely acknowledged in prior work (e.g., Robertson et al. 2001; Trauth 2013), no specific statistics on gender distribution in the BPM workforce or composition of BPM teams could be identified. There also appears to be a paucity of BPM research addressing the topic of gender. Our study, thus, initiates a discussion on the topic of gender imbalance in the BPM field and builds foundations for further research on gender and BPM. Addressing the underrepresentation of women might be one way to mitigate the shortage of qualified BPM professionals.

One major limitation of our study is that the analyzed competences are self-reported and it was not possible to test whether the professionals forming our dataset indeed possessed the presented competences. Here, however, competence endorsements can act as a control mechanism. We are also aware that the information provided by LinkedIn members may be inaccurate, partially exaggerated, or simply not true. However, we believe that after the thorough data cleansing, a reliable set of profiles was analyzed. Moreover, if some of the profiles in the analyzed sample are indeed falsified, they should not bias the results, as (1) their number should be very low and (2) we see no reason for business process-related competences to be over- or underrepresented in fake profiles. We also acknowledge that the analyzed profiles might differ from traditional CVs of candidates that are used to apply for a specific BPM-related position. Despite these limitations, we consider our dataset as suitable for gaining first insights into supplied BPM competences.

According to a study by Robert Half Inc. (no author 2013), there could be bias towards younger workers among LinkedIn members compared to the overall workforce. Although the profiles do not contain information about age, we assume that there is a high correlation with the reported work experience. The average value here was 16 years with the standard deviation of 8 years and 50.8 % of analyzed profiles indicated more than 15 years of work experience. Therefore, we assume that in our sample both younger and older employees are well represented.

We have performed a hierarchical analysis of the current positions. Apart from this *vertical* analysis, a *horizontal* (content) analysis of both current and previous positions could bring additional insights into the nature of work done by BPM professionals.

Future research should also go beyond the *Western* perspective taken in this study and investigate the BPM workforce in, for example, Eastern European and Asian societies, performing a cross-cultural analysis. The study findings could diverge if different cultures were analyzed. At the same time, we are confident that the four English-speaking countries represent a good starting point for this initial analysis. Moreover, a cross-industry analysis of BPM-related competences offered by employees working in fields not covered in this study could be done in the future.

Thus, our study provides a starting point for further research on human capital, the underrepresentation of women, and the competence gap in the BPM field. The findings are also of value for BPM practitioners and especially for recruiters of BPM staff. They may incorporate our findings in their hiring practices and build on (a) the awareness of the underrepresentation of women in the BPM workforce and the need to make BPM teams more diverse; (b) the evidence that female BPM professionals tend to present their competences differently to men working in BPM; and (c) the proposed interventions for addressing the competence gap in the field. Understanding the gap between self-reported and demanded competences in the BPM field is helpful for both the employees who would like to enter the BPM workforce and for educators to further develop BPM curricula. For employees, the communication of such competences in their CVs and public profiles on professional online social networks, like LinkedIn, may result in gaining a competitive advantage, as organizations have an interest in these competence sets. At the same time, educators may use the findings of our study to ensure that BPM curricula at their academic institutions facilitate the learning of a holistic set of competences to include those that seem to be underrepresented in the current labor market.

Acknowledgments This work is part of a project that has received funding from the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie Grant agreement No 645751. Any opinions, findings, and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the European Commission. We gratefully acknowledge the support of Ms. Megha Anand during the data collection process.

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