

# A GENDER PERSPECTIVE ON BUSINESS PROCESS MANAGEMENT COMPETENCES OFFERED ON PROFESSIONAL ONLINE SOCIAL NETWORKS

*Complete Research*

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## Abstract

*While Business Process Management (BPM) originally strongly focused on Information Technology as a key factor driving the efficiency and effectiveness of organisational processes, there is a growing consensus that BPM represents a holistic management approach that also takes factors like corporate governance, human capital and organisational culture into account. Focusing on human capital, our exploratory study examines competences supplied in the BPM field and how far they represent the holistic nature of BPM. Further, our study tries to understand, whether the BPM field, which is traditionally perceived as very technical, is not immune to the challenge of female underrepresentation. Addressing underrepresentation of women in BPM would help to mitigate the existing competence shortage in the field that stems from the lack of qualified BPM professionals. Thus, we take a gender perspective in analysing 10,405 BPM-related LinkedIn profiles using a text mining technique called Latent Semantic Analysis (LSA). We identify 12 distinct categories of competences supplied by BPM professionals, which, in general, reflect the interdisciplinary nature of BPM, ranging from technical to managerial and domain-specific competences. Analysis of the gender distribution shows that women are underrepresented among the BPM professionals under study and, in particular, among those representing most of the identified categories of competences.*

*Keywords: business process management, competence analysis, LSA, gender diversity, BPM workforce.*

## 1 Introduction

Business Process Management (BPM) is “an interdisciplinary approach to the analysis, design, implementation, and improvement of organisational work processes and supporting Information Technology (IT) systems” (Müller et al., 2014, p. 1). It is one of the most prominent academic and professional areas in the Information Systems (IS) field (vom Brocke and Rosemann, 2014; Roberts and Sikes, 2011). According to Gartner’s CIO (Chief Information Officers) studies, improvement of a company’s business processes has remained one of the top priorities for almost a decade (Gartner, 2011). Historically driven by the Business Process Re-Engineering approaches (e.g., Davenport, 1992; Hammer and Champy, 1993), BPM used to focus on the opportunities offered by IT systems for the radical re-design of a company's business processes along the complete value chain (Altinkemer et al., 2011; Hammer, 2011). In recent years, however, the understanding of BPM has developed into a holistic management philosophy, which, besides IT, also takes aspects like corporate governance, human capital and corporate culture into consideration (Rosemann and vom Brocke, 2010). This holistic approach to

BPM is expected to gain even more importance in the upcoming years (Gartner, 2014a). However, especially in academia, BPM still focuses on a rather technical aspects, such as workflow optimization or process modelling (e.g., Dumas et al., 2013; Schmiedel et al., 2014) evidenced by, for example, the majority of papers published in proceedings of BPM-focused conferences (BPM Conference Series, 2014). At the same time, critical success factors of BPM projects are found to be mostly non-technical (Trkman, 2010).

In line with the recently developed holistic understanding of BPM, companies are aware that BPM projects require diverse competences that need to be provided by a broad variety of BPM professionals (Lee et al., 2000; Müller et al., 2014). However, recent studies confirm that it is often hard to find enough qualified employees to fill the opened positions in particular BPM areas (Gartner, 2013). Furthermore, employees already working in the field often seem to not deliver the full set of competences necessary for successful BPM implementations (Bandara et al., 2010; Gartner, 2008). Therefore, the resulting gap between competence supply and demand might be caused by the lack of both personnel in the field and competences that BPM employees offer.

While extant research has already identified what specific skill sets employers require from BPM professionals (Davis et al., 2003; Müller et al., 2014), to the best of our knowledge, the competences offered by professionals in the BPM field have not been thoroughly investigated yet. Against this background, the purpose of our study is to provide a detailed understanding of competences currently supplied by BPM professionals, which would then allow specifying BPM competence gaps. Understanding these gaps could be helpful for students who plan to enter the BPM job market, as well as for educators to further develop BPM curricula.

In examining competences offered by BPM professionals, the gender distribution among them is also investigated in this study. Our goal here is to understand, whether the BPM field, which is traditionally perceived as very technical, is not immune to the challenge of female underrepresentation, as it is the case in the IT field. If underrepresentation of women in BPM exists, addressing it could help to mitigate the existing workforce shortage of qualified professionals in the field. Balancing the gender ratio in the BPM field would also make BPM teams more diverse, which, on the one hand, would lead to their “superior productivity and financial performance compared with homogeneous teams” (Barker et al., 2014, p. 2), and, on the other hand, act as a social good raising equity in the opportunities men and women have in pursuing their careers (Trauth, 2011).

In our exploratory study we, therefore, address the following questions:

1. What categories of competences are currently supplied by BPM professionals?
2. What is the gender distribution among BPM professionals?

In order to answer these questions, we used Latent Semantic Analysis (LSA), a text mining technique, to analyse 10,405 BPM-related profiles of professionals collected from LinkedIn<sup>1</sup>, “the world's largest professional online social network” (Bastian et al., 2014, p. 1). In particular, we examined the reported competences and corresponding numbers of endorsements and connections, work experience, as well as the gender distribution in the analysed profiles.

The remainder of the paper is structured as follows. In the next section we provide some background information about BPM competences, the challenges related to the lack of BPM competences and BPM professionals, as well as outline the appropriateness of using LinkedIn profiles as a data basis for our study (Section 2). Afterwards, we describe the process of profile collection, information extraction and data pre-processing (Section 3). The steps for data analysis, in particular, a description how the LSA technique was applied, are reported afterwards (Section 4). Our results are presented in the subsequent section (Section 5) followed by their discussion (Section 6). The study outcomes and areas of future research are summarised in the concluding section (Section 7).

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<sup>1</sup> [www.linkedin.com](http://www.linkedin.com)

## 2 Background

### *BPM Competences*

In our study, we understand the term *competence* as a *work-related knowledge, skill or ability* held by an individual (Nordhaug, 1993). While the terms *knowledge, skill and ability* have different connotations, empirical IS studies often use them interchangeably (Müller et al., 2014), as it is also done in this paper.

Extant studies on BPM competences often focus on organisations as a unit of analysis. For example, studies on maturity models concentrate on organisational BPM capabilities (Van Looy et al., 2013), examining what competences should be improved or added to the project or company in order to advance BPM efficiency.

However, there are not many studies focusing on the competences for conducting successful BPM projects that are required and offered on an individual level. The exceptions here are the studies of Bandara et al. (2009), Launonen and Kess (2002), and Müller et al. (2014). The latter study of Müller et al. (2014), for example, examines the demand from organisations for specific BPM competences and presents a set of seven ideal types of BPM professionals derived from analysis of online job advertisements. Several other earlier studies also used sources of data like job advertisements published in newspapers and journals or websites of IT corporations to examine the competences required by organisations (e.g., Petrova and Medlin, 2006). While there are several studies specifying what competences are necessary for successful implementation of BPM projects, there still seems to be a lack of research on BPM competence supply.

### *Shortage of BPM competences and qualified BPM professionals*

Several academic studies have identified an existing shortage of BPM competences (Mathiesen et al., 2013) that stems from the shortage of qualified BPM professionals (Antonucci and Goeke, 2011; Bandara et al., 2010). Similar challenges exist in IS in general (Gareis et al., 2014): According to the “e-Skills for Jobs in Europe” study done by the European Commission (EC), Europe might face a shortage of up to 900,000 IS professionals by 2020 (European Commission, 2014). A similar trend has been recently announced by the United States (US) Bureau of Labor Statistics, forecasting that within the period 2012-2022 there will be 1.24 million IT-related job openings – a demand that cannot be satisfied with the forecasted number of IT graduates (U.S. Bureau of Labor Statistics, 2013a). Although the exact figures are arguable, it is hard to decline existence of these challenges in IS in general and in BPM in particular.

Mathiesen et al. (2013) analysed the Australian BPM market in order to align it with the national BPM education. In their study, they refer to Rosemann (2010), who expects a “broad range of skills such as subject domain knowledge, workshop facilitation, change management, and even creativity” from BPM practitioners and conclude that these competences are “more commonly expected at the postgraduate level” (Mathiesen et al., 2013, p. 478). This indicates that BPM requires highly trained people, who are not yet well-represented in the BPM field. The same challenge holds true in countries like South Africa (Sonteya and Seymour, 2012) or Brazil (Alves et al., 2014). Furthermore, studies report on existing gaps between the BPM competences taught at universities and those that are required in practice (Lee et al., 2002). A recent study done by Gartner calls for attention to BPM skills related to organisational change and to focus less on traditional BPM skills, such as process modelling (Gartner, 2014b). The same study also raises awareness about the importance of competences related to articulation and communication of business value and process-related issues.

### *LinkedIn Profiles as a data source for the competences supplied by BPM professionals*

A profile published on a professional online social network (such as XING<sup>2</sup> or LinkedIn) typically contains information about current and previous positions, education, competences, interests, etc.,

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<sup>2</sup> [www.xing.com](http://www.xing.com)

having, therefore, a similar structure to a traditional Curriculum Vitae (CV). Several earlier studies admit a great research potential of CVs as a source of data for understanding a 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 rather reluctant to share them. At the same time, public profiles created by members of professional online social networks are easy to access, allowing a collection of large volumes of data. Moreover, online platforms offer additional features, like endorsements or theme groups, which provide more detailed information about individuals than traditional CVs.

Online profiles have already been analysed in earlier studies on individual competences. For example, Chelaru et al. (2014) analysed the profiles extracted from About.me, LinkedIn, Twitter, and Facebook to understand “how skills in professional networks are related and [how to] categorise these skills into professions” (p. 1). In another study of Joseph et al. (2005) individual IT career paths based on profiles extracted from the National Longitudinal Survey of Youth (NLSY) dataset were analysed.

### 3 Profile Collection and Pre-processing

#### 3.1 Profile Extraction

In order to address the study goals, we first collected member profiles from LinkedIn – “the world's largest professional online social network” (Bastian et al., 2014, p. 1). Apart from the general applicability of social network data for research purposes, we chose this platform to collect information on competences supplied by people who are considered to have expertise in the BPM field (called ‘BPM professionals’ hereinafter) due to the two following reasons. 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 in-built LinkedIn search engine allows finding people with competences in the BPM field. Second, as each profile contains a member’s first and last name and usually also a picture, there is an opportunity to identify gender of selected members in order to then analyse the sample gender distribution.

We collected data in autumn 2014 storing profiles as semi-structured HyperText Markup Language (HTML) files. The free basic LinkedIn account allows one to get a maximum of 100 *hits per search query*, which we deemed not enough to fulfil the purpose of our study. In order to be able to collect a higher number of profiles, we used a paid premium account, which increases the amount of *hits per search query* to 500. As the total number of profile downloads per day was limited, the data collection process took one month. The maximum of 500 *hits per search query* is valid for each combination of filters offered by LinkedIn. The returned profiles are automatically ordered by relevance based on a search term, meaning that for each query the top 500 relevant profiles are delivered. 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 several factors.

The search was done for people’s profiles containing the term ‘business process’. 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.

The profiles were searched in developed English-speaking countries, namely in the United States (US), 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, which makes it possible to analyse them within a single dataset. Finally, we agreed that we first should concentrate on profiles originally created in English, rather than translated into English automatically by LinkedIn. We believe that such a choice makes the profiles more comparable.

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 with the largest total number of relevant profiles in the four countries mentioned above: Computer Software, IT and Management Consulting.

In order to further increase the number of hits and to gain an opportunity to compare the profiles across companies in our future research, 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.

Application of these filters gave an opportunity to access up to 24,000 distinct profiles satisfying the search criteria (4 countries \* 3 industries \* 4 companies \* 500 available profiles in each search iteration = 24,000). However, many combinations of filters returned less than 500 hits. Furthermore, as each profile was saved manually, some of them later turned out to be stored in a wrong format and could not be processed further. As a result, 14,923 usable profiles could be collected.

### 3.2 Information Extraction from the Profiles

In order to extract relevant information from the profiles, we wrote a PHP (PHP Hypertext Preprocessor) script applying Regular Expressions. The following semi-structured data was derived from each of the 14,923 stored HTML files: full name, current and past jobs (including start dates, company names and positions), number of LinkedIn peer connections (up to 500 connections could be tracked; if a profile contained more connections, a tag “500+” was returned), competences (called “Skills” by LinkedIn; each LinkedIn member can add up to fifty areas of expertise to his/her profile) and number of endorsements for each competence. For each profile we could identify the first year and, for the majority of profiles, also the first month of employment (or assumed it to be January if no month was mentioned). Based on this information, we calculated the total work experience in months with November 2014 being the current month.

In order to identify 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 JavaScript Object Notation (JSON) object with 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. All cases with the gender certainty below 50% (ranging from -0.5 to 0.5) were manually screened and, where necessary, corrected or removed (see the Data Cleansing subsection for further details).

Finally, the script tagged the profiles where ‘business process\*’ was mentioned among competences in order to facilitate further analysis.

### 3.3 Profile cleansing

Once the information was extracted into a comma-separated values (.csv) file and converted into an Excel table, we cleansed it.

Several cases had identical first and last names and 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.

Cases with unknown or uncertain gender were manually screened and the initial HTML files of all doubtful profiles were investigated. 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). Unfortunately, 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 evidently 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 decided to remove 4,377 profiles, where the search term ‘business process’ did not appear as one of the areas of expertise.

Finally, we removed 95 cases with missing information about the start dates of working at previous and current jobs, as it was not possible to calculate the total months of experience for them. Although work experience of the selected members was not the major focus of the current study, we would like to investigate it further in our future research and, therefore, decided to exclude the incomplete cases at this stage already.

All numerical fields were also checked for outliers. Several cases contained positions dating back to 1,900, which were considered as typos 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 which were examined further.

## 4 Data Analysis

### 4.1 Study Sample

Table 1 summarises descriptive statistics of the study sample, including male / female ratio in countries and industries under investigation. The majority of selected members were from the US (35.5% of the overall sample), which is in line with the overall LinkedIn statistics (LinkedIn Corporation, 2014).

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%	1,176	11.3%
	Management Consulting	735	69.3%	325	30.7%	1,060	10.2%
Total United Kingdom		1,898	74.1%	665	25.9%	2,563	24.6%
United States	Computer Software	798	72.5%	303	27.5%	1,101	10.6%
	IT	1,066	74.6%	363	25.4%	1,429	13.7%
	Management Consulting	830	71.1%	337	28.9%	1,167	11.2%
Total United States		2,694	72.9%	1,003	27.1%	3,697	35.5%
Australia	Computer Software	116	75.8%	37	24.2%	153	1.5%
	IT	910	70.8%	376	29.2%	1,286	12.4%
	Management Consulting	506	68.3%	235	31.7%	741	7.1%
Total Australia		1,532	70.3%	648	29.7%	2,180	21.0%
Canada	Computer Software	143	73.3%	52	26.7%	195	1.9%
	IT	862	69.3%	381	30.7%	1,243	11.9%
	Management Consulting	362	68.7%	165	31.3%	527	5.1%
Total Canada		1,367	69.6%	598	30.4%	1,965	18.9%
Total Computer Software		1,325	74.6%	451	25.4%	1,776	17.1%
Total IT		3,733	72.7%	1,401	27.3%	5,134	49.3%
Total Management Consulting		2,433	69.6%	1,062	30.4%	3,495	33.6%
Total		7,491	72.0%	2,914	28.0%	10,405	100%

Table 1. Study Sample and its Gender Distribution

During the analysis of the final study sample, our first observation was that female profiles comprised only 28% of it, which shows a clear male domination. It was necessary to compare this number with the share of women among all LinkedIn members in the selected countries. This information was derived from the Quantcast portal<sup>3</sup>, which provides member demographic data of various social networking websites.

It turned out that there are in general more men among LinkedIn members, with the following shares of women: 35% in the UK (vs. 25.9% in our sample), 40% in the US (vs. 27.1% in our sample), 29% in Australia (vs. 29.7% in our sample), and 36% in Canada (vs. 30.4% in our sample). It is interesting that for Australia the share of women in our sample is a little bit above the country average. Nevertheless, based on *t*-statistics test done with *SPSS 21*, the share of women in our study sample (28%) is significantly lower (significance at the .001 level) than the average share of women in four analysed countries (35%).

Based on this finding, we can conclude that in our dataset of employees, who are considered to have expertise in the BPM field, women are underrepresented. This result can also be explained by the domination of profiles from the IT industry (49.3% of the overall sample), where the share of women is generally low (e.g., U.S. Bureau of Labor Statistics, 2013b). This finding indicates that the challenge of female underrepresentation seems to also be present in the BPM workforce.

The largest share of women was observed in the profiles from Canada (30.4%) and the Management Consulting industry (30.4%).

## 4.2 Latent Semantic Analysis of the competences supplied by BPM professionals

Analysis of CVs has traditionally been done manually, which made the process costly and subject to many limitations. Modern technologies allow automatic analysis of large amounts of electronic CVs, allowing for more consistent and precise results (Bhargavi et al., 2008). One such text mining technique, Latent Semantic Analysis (LSA), was applied in our study.

LSA is a quantitative method for analysing qualitative data, which has received a growing attention in the IS discipline over the last years (e.g., Evangelopoulos et al., 2012; Landauer et al., 1998). The underlying idea is that the contexts (LinkedIn profiles in our case) in which words (competences mentioned in each profile) occur and co-occur largely determine the words' meaning.

The goal of the performed LSA was to gain a deeper understanding of what categories of competences are offered by BPM professionals forming our dataset. Moreover, we were interested in the gender distribution among the most representative profiles for each competence category.

The first step in the analysis was building a competence-profile matrix containing the number of times each competence appeared in each profile (Manning et al., 2008). We could identify 3,998 different competences in 10,405 collected profiles. Following the general LSA process (e.g., Evangelopoulos et al., 2012), we then performed a dimensionality reduction operation called singular value decomposition (SVD) on the competence-profile matrix using the statistical computing software *R*. This approach is similar to traditional exploratory factor analysis and produces so-called latent semantic factors, each represented by a vector of high-loading profiles and high-loading competences. These factors represent clusters of words (competences) that co-occur in groups of similar documents (profiles).

After exploring 10-, 12-, 15-, 20-, 25-, and 30-factor solutions, it was decided to select 12 factors for further interpretation, as the solutions with higher number factors contained more and more near duplicates (very similar factors).

As a next step, high-loading terms and high-loading profiles were extracted for each factor (Evangelopoulos et al., 2012). 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

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<sup>3</sup> [www.quantcast.com](http://www.quantcast.com)

was selected for this study ( $k = 12$ ), 8.3% of high-loading terms and profiles were derived for further analysis.

The list of top 333 extracted competences for each factor (8.3% of total 3,998 competences) was independently analysed by four researchers. Each researcher had to screen them, suggesting the most representative label for each factor. The labels provided by four researchers 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 Results section.

Moreover, the gender distribution was investigated in top 867 profiles for each factor (8.3% of total 10,405 profiles). The goal was to understand, whether there are significant differences in gender distributions between high-loading profiles forming each factor and the overall study sample. Therefore, *t*-statistics were calculated between the respective mean values. The outcomes of this analysis are also discussed in the Results section.

### 4.3 Further Insights into the Study Sample

In order to get a more profound understanding of the study sample, we explored the significance and effect sizes of associations between other variables forming our dataset, which gave us additional insights into the collected profiles and supported us during further interpretation of the LSA results. The extracted profiles contained information about gender, location, industry, months of experience and number of connections. Moreover, based on the information about competences and number of endorsements for each competence, it was possible to calculate the total number of competences and the sum of endorsements for each profile. The following tests and measures were performed with *SPSS 21*:

- *One-way ANOVA* (Analysis of Variance) tests with *Eta Squared* to measure the association between the gender dichotomous variable and such interval variables as number of competences, sum of endorsements, months of experience and number of connections (e.g., Pierce et al., 2004). We assume the gender variable to be independent and the interval variables to be dependent.
- *Pearson (r)* correlation coefficients to measure the association between the above-mentioned interval variables (e.g., Pearson and Galton, 2012).
- *Chi-squared* test with *Cramer's V* ( $\phi_c$ ) to measure the association between gender and such nominal variables as location and industry (e.g., Pallant, 2010). The results of this analysis, however, were negligible and, therefore, are not discussed further.

The outcomes of *one-way ANOVA* tests revealed that in our sample women on average tag fewer competences than men, have fewer endorsements, connections, and months of experience (Table 2). And although all effect sizes measured by *Eta Squared* are small, they are statistically significant at the .01 level. These results were supported by both Welch and Brown-Forsythe robust tests of equality of means, which were statistically significant at the .001 level (Pierce et al., 2004).

Some other interesting relationships were identified between the interval variables measured by *Pearson (r)* correlation coefficients (Table 2). The first finding, which is not very surprising, is that the Sum of Endorsements construct has strong positive correlations with both Number of Competences ( $r = .645$ ) and Number of Connections ( $r = .546$ ), as well as moderate positive relationship with Months of Experience ( $r = .323$ ). In other words, the total number of endorsements (as a measure of expertise) increases with higher numbers of reported competences (the more competences one has, the more total endorsements one receives), connections (as the business contacts form the pool of potential endorsers) or work experience (expertise raises with experience). Second, there are weak, but still significant positive associations between Months of Experience and both Number of Competences ( $r = .238$ ) and Number of Connections ( $r = .128$ ). This finding is also logical, as with experience one usually gains more expertise and extends a network of business contacts. Third, there is a moderate positive

correlation between Number of Connections and Number of Competences ( $r = .382$ ). This finding, in our opinion, is related to the activity of LinkedIn members: Active members probably tag themselves on average with more competences and connect with more other members than passive members. It would, therefore, be interesting to analyse the relationship between these variables and the related frequency and duration of using LinkedIn.

The fact that women on average tag less competences in their profiles than men does not implicate that they have less expertise, but rather might be caused by their lower confidence and self-efficacy in comparison with men, which is in line with previous research (Institute of Management & Leadership, 2011; Litzler et al., 2014; Sandberg, 2013; Sturm et al., 2014). Lower average sum of endorsements is a consequence thereof.

Previous studies in the IT field also report on the so-called ‘old boys’ network’ phenomenon, meaning that the people working in the IT field, mostly men, tend to build professional connections with those similar to them, i.e. other men, thus excluding women (e.g., Loiacono et al., 2013; Trauth, 2013). As predominantly IT employees have formed our dataset, this might be a possible explanation, why women in our sample have on average fewer connections than men. Having less 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.

We could not find academic studies, which could help us to explain the fact that women on average have fewer months of experience. One possible reasoning here could be that traditionally women take (longer) parental leave and, therefore, are out of workforce for a longer time than men.

	Mean Value		<i>Eta Squared</i>	<i>Pearson's (r)</i>		
	Men	Women		Sum of Endorsements	Number of Connections	Months of Experience
Number of Competences	25.98	22.77	.013**	.645**	.382**	.238**
Sum of Endorsements	163.57	127.07	.012**		.546**	.323**
Number of Connections	341.14	298.43	.016**			.128**
Months of Experience	200.88	183.62	.006**			
** - significance at the .01 level						

Table 2. Significance and Effect Sizes of Relationships between Variables in the Study Sample.

## 5 Results

LSA has confirmed to be a reliable instrument when dealing with large volumes of textual data. Interpretation of the 12-factor solution derived by employing the LSA method has resulted in 12 clearly distinguishable categories of competences supplied by BPM professionals, which are summarised in Table 3 and discussed in the following paragraphs:

[1] *Strategic Management*: The typical competences forming this category are related to higher management qualifications (e.g., Business Transformation, Management Consulting, Change Management, or Program Management).

[2] *(IT) Project Management*: The competences comprising this category span over 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).

[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*. High-loading competences for Category [4] include *SAP R/3*, *SAP Implementation* and other *ERP*-related competences like *SAP for Order-to-Cash* or *SAP for Retail*. Category [5] consists of competences related to *Oracle* solutions, such as *Oracle e-Business Suite*.

[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.

[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 (e.g., *IT Service Management* or *IT Outsourcing*).

[8] *Business Intelligence*: The competences making up this category are related to different aspects of storing, maintaining and analysing corporate data. They include such technical and software-related competences as *SQL (Structured Query Language)* or *Cognos*, as well as conceptual competences (e.g., *data modelling* or *data warehouse architecture*).

[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 (General Accepted Accounting Principles)* or *ISO 27001* and governance mechanisms (e.g., *Sarbanes-Oxley Act*). Furthermore, the category includes such risk management competences as *security* and *disaster recovery*.

[10] *Accounting and Finance*: The category comprises finance-related competences at managerial (e.g., *Corporate Finance*, *Financial Accounting*), conceptual (e.g., *Financial Modelling*), or operative (e.g., *Forecasting*, *Financial Analysis*, *Reporting*) levels.

[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 Optimization*, or *Process Improvement*).

[12] *Human Resource (HR) Management*: The competences of this category deal with the organisation of corporate human resources (human capital). Most of them are related to management (e.g., *Talent Management*, *Personnel Management*, *Organisational Design*). Some also focus on operative HR tasks (e.g., *Training*, *Recruiting*, *SAP HR*), as well as changes in a corporate culture.

We believe that the identified categories represent the variety and heterogeneity of areas in the BPM field, spanning 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 (described, for instance, in the book of vom Brocke and Rosemann, 2010) might not have been covered to its full extent. Moreover, the domination of technical categories can be observed (Categories [3]-[7]), which shows that BPM is still a rather technical field in practice.

Besides high-loading competences, we also analysed high-loading profiles (top 867 profiles) for each factor, concentrating on gender distribution in them (see Table 3). High-loading profiles are those that best represent each of the twelve identified factors. A series of *t*-statistics tests were performed, where the share of women among high-loading profiles forming each factor was compared to the share of women in the overall study sample (28%). The results show that for 10 out of 12 categories the share of women among high-loading profiles is lower than in the overall study sample, meaning that more male than female profiles represent the absolute majority of categories of competences. Exceptions can be observed in the (IT) *Project Management* and *HR Management* categories, containing 29.4% and 39.4% of women respectively, which is higher than the 28% share of women in the overall study sample. Only

for eight (out of twelve) factors such 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, where the higher share of women than in the overall sample is statistically significant is HR Management (Table 3). This can be explained by the rather non-technical nature of HR, compared to the other categories.

Nr.	Category of Competences	Examples of High-Loading Competences	Deviation in the Share of Women in High-Loading Profiles from the Study Sample (28%)
[1]	Strategic Management	Business Transformation, Requirements Analysis, Change Management, IT strategy, Program Management	-1.8%
[2]	(IT) Project Management	Project Delivery, ITIL, PMO, Stakeholder Management, Project Portfolio Management	+1.4%
[3]	Enterprise Architecture	Business Process Design, SOA, Organisational Design, Enterprise Architecture, EAI (Enterprise Application Integration)	-4.8% **
[4]	ERP Solution Architecture (SAP)	SAP R/3, SAP Implementation, ABAP (Advanced Business Application Programming), SAP NetWeaver, SAP BW	-6.0% ***
[5]	ERP Solution Architecture (Oracle)	Oracle e-Business Suite, Oracle Applications, ERP, Oracle, Oracle HR (Human Resources)	-3.7% *
[6]	Software Development	SDLC (Systems Development Life Cycle), Requirements Gathering, Software Project Management, Solution Architecture, Agile Methodologies	-8.3% ***
[7]	IT Service Outsourcing	Service Delivery, Outsourcing, IT Service Management, IT Outsourcing, Software as a Service (SaaS)	-3.4% *
[8]	Business Intelligence	Data Analysis, Data Warehousing, ETL (Extract, Transform and Load), Master Data Management, Business Objects, SQL (Structured Query Language)	-1.9%
[9]	Auditing and Risk Management	Internal Controls, Internal Audit, Enterprise Risk Management, IT Audit, Risk Management	-2.7%
[10]	Accounting and Finance	Financial Modelling, Financial Analysis, Financial Reporting, Corporate Finance, Managerial Finance	-3.2% *
[11]	Supply Chain Management	Supply Chain Management, Supply Chain, Procurement, Strategic Sourcing, Logistics	-5.5% ***
[12]	HR Management	Talent Management, Performance Management, HR Transformation, Employee Engagement, Personnel Management, Culture Change	+11.4% ***
* - significance at the .05 level; ** - significance at the .01 level; *** - significance at the .001 level			

Table 3. Categories of competences supplied by BPM professionals (12-factor solution).

## 6 Discussion

### *The nature of the identified competences supplied by BPM professionals*

Diversity of the twelve BPM-related categories of competences, which were revealed by applying the LSA method, shows that the professionals forming our dataset provide competence sets that represent the interdisciplinary nature of BPM. It is, therefore, possible to map the categories to the well-established areas in the BPM field, summarised e.g. in the BPM Maturity Model introduced by vom Brocke and Rosemann (2010). The six pillars of the model comprise both technical and managerial areas of BPM, which include strategic alignment, governance, methods, IT, people, and culture (vom Brocke and Rosemann, 2010). Each of them can be related to one or more categories we have identified: For example, strategic management [1] supports capabilities in strategic alignment; business intelligence [8] and auditing [9] competences foster governance capabilities; project management [2] offers 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 culture. Beyond covering specific facets of BPM in general, the identified categories also contain such domain-specific knowledge areas as accounting and finance [10] or supply chain management [11].

While the observed competences are of both technical, managerial, and domain-specific nature, the findings show a slight domination of IT-related categories of competences (five out of 12 competence areas, namely, Categories [3]-[7]). This fact shows that BPM is still very technical in practice today, although, according to Hammer (2011), IT “is at most a peripheral aspect of BPM” (p. 3).

Although our results show a broad range of competences being offered by BPM professionals, we, nevertheless, argue that the holistic nature of BPM might not have been covered to its full extent. For example, research has found that cultural competences in BPM include establishing values such as internal and external customer orientation and cross-functional teamwork (Schmiedel et al., 2013) – aspects not occurring in the identified competence categories.

### *The challenge of underrepresentation of women in BPM*

Results show the underrepresentation of women in the study sample in comparison to the average share of women among LinkedIn members in the selected countries. Here we need to admit that in general only 35% of LinkedIn members in four countries under investigation are women, so the relative underrepresentation of women (-7%) is not extremely high, although still significant.

Study results also show a low share of women in profiles representing most categories of competences. Significant male domination was revealed in seven out of 12 categories and in all five IT-related categories (Categories [3]-[7]). The latter finding is not surprising, as extant research and statistics show that involvement, retention and advancement of women in IT remains an acute challenge in western societies (e.g., Gorbacheva et al., 2014; Trauth, 2011). According to statistics, women are underrepresented in the IT field in all four countries under investigation: Among IT specialists women comprise less than 16% in the UK (e-Skills UK, 2014), 20% in Australia (Australian Workforce and Productivity Agency, 2013), 24% in Canada (Sankey, 2014), and 26% in the USA (NCWIT, 2014).

Existing shortage in BPM professionals (Lee et al., 2000) and underrepresentation of women in the field revealed by our study show that there is a need for enriching BPM workforce by motivating more qualified women to enter it. As earlier studies show that people tend to choose jobs represented by those similar to them (e.g., Barbulescu and Bidwell, 2012), more visible female role models who work in the BPM field could motivate other women to choose a career in BPM. Moreover, interventions programs creating awareness about the wide range of career opportunities in BPM should be encouraged on a number of levels (with pupils, students and employees as target audiences). Such programs should also aim at increasing women self-efficacy and confidence: We assume that self-efficacy and confidence could be valid reasons explaining our finding that women tend to tag in their LinkedIn profiles significantly fewer competences than men. This assumption is based on previous research, including the studies of the Institute of Management & Leadership (2011), Litzler et al. (2014), Sandberg (2013), and Sturm et al. (2014).

### *Limitations*

Our study is of an exploratory nature and the findings might differ if, for instance, different countries were analysed. At the same time, we are confident that the four English-speaking countries were the right starting point for this initial analysis.

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 performed thorough data cleansing, a reliable set of profiles was analysed. And even if there are still some fake profiles in the analysed sample, we expect them to 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 under-represented in fake profiles.

We also admit that the analysed profiles might differ to CVs of candidates applying for a specific BPM-related position, where they might present only sub-set of their skills that they feel is relevant for this particular occasion.

According to Half (2013), there might be a bias towards younger workers among LinkedIn members compared to the overall workforce. As the profiles do not contain information about age, we had a look at the reported work experience instead and the average value here was 16 years with 50.8% of members having more than 15 years of work experience. Therefore, we assume that in our sample both younger and older employees are well represented.

## **7 Conclusion and Outlook**

The first goal of this exploratory study was to identify the categories of competences supplied by BPM professionals. Here LSA was employed as a text mining method for analysis of 10,405 BPM-related LinkedIn profiles and, as a result, twelve categories of competences offered by people who are considered to have expertise in the BPM field were revealed. Although these categories are quite diverse, they, nevertheless, might not fully represent the holistic nature of BPM. Further exploration of BPM competence gaps, i.e. the breach between competence supply and demand, is subject to future research.

The second goal was to understand, whether women are underrepresented in our study sample, which can be then extrapolated to BPM workforce in general in the four countries under investigation (as no specific statistics of gender distribution in the BPM field could be found). Here gender distribution was analysed both in the overall study sample and in the profiles representing each competence category. In both cases women turned out to be underrepresented, although not as dramatically as in the IT or other STEM (Science, Technology, Engineering, and Mathematics) fields. To the best of our knowledge, gender distribution in BPM workforce has not been thoroughly investigated in previous research. In future studies it would be interesting to compare the gender distribution and skill sets between the ‘younger’ and the ‘older’ generations of BPM professionals, based on their work experience. Cross-company analysis between the four selected enterprises might bring additional insights.

The collected LinkedIn profiles contain further aspects, which were not in scope of the current study, but are worth being analysed in the future. One example here is information about education, which could also be extracted from each profile. Extant research on BPM education is usually based on interviews or analysis of curricula and has not been yet investigated using CVs of online profiles of people working in the field. Examining education of people forming our dataset in combination with their career paths and sets of offered competences might provide important insights for both BPM educators and students.

Future research should also go beyond the ‘western’ perspective taken in this study and investigate BPM workforce in e.g. Eastern European and Asian societies, performing a cross-cultural analysis. Moreover, cross-industry analysis of BPM-related skills offered by employees working in the fields not covered in this study could be done in the future. Next, in our study we concentrated on the extracted structured data and did not analyse the overall impression each profile leaves, which forms another promising area for future research. Finally, application of a different method, e.g. interviews with some of the people forming our dataset, could enhance our understanding of the study findings and provide further insights.

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