Knowledge Hubs in Competence Analytics: With a Case Study in Recruitment and Selection

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Abstract: There is a lack of consensus on the usefulness of Human Resource (HR) analytics to achieve better business results. The authors suggest this is due to lack of empirical evidence demonstrating how the use of data in the HR field makes a positive impact on performance, due to the detachment of the HR function from accessible data, and due to the typically poor IT infrastructure in place. We provide an in-depth case study of Strategic Competence analytics, as an important part of HR analytics, in a large multinational company, labelled ABC, which potentially shows two important contributions. First, we contribute to HR analytics literature by providing a data-driven competency model to improve the recruitment and selection process. This is used by the organization to search more effectively for talents in their knowledge networks. Second, we further develop a model for data-driven competence analytics, thus also contributing to the information systems literature, in developing specialized analytics for HR, and by finding appropriate forms of computerized network analysis for identifying and analysing knowledge hubs. Overall, our approach, shows how internal and external data triangulation and better IT integration makes a difference for the recruitment and selection process. We conclude by discussing our model's implications for future research and practical implications.

1 INTRODUCTION

Human Resource (HR) analytics is a relatively young and underexplored research field under the umbrella of Big Data Analytics (BDA) (Batistič and Van der Laken, 2018). HR analytics enables organizations to use descriptive, visual, and statistical analyses of data related to HR processes to establish business impact and enable data-driven decision-making (Marler and Boudreau, 2017). Empirical evidence showing the beneficial role of HR analytics in the HR function and in the organization, in general, is scarce (e.g., Van den Heuvel and Bondarouk, 2016; Marler and Boudreau, 2017). Various potential pitfalls why HR analytics fails to deliver have been identified, but there seems to be consensus, that the HR Information Technology (HR IT) might limit its function as an HR analytics inhibitor: data could be inaccurate, inaccessible, outdated, lack depth, could not have been collected at all, or could not be integrated across function, geography or department (Marler and Boudreau, 2017). Especially combining internal and external data could provide challenges and pitfalls, such as poor comparability among others (Brown and Vaughn, 2011). Improvements should be made in HR IT to improve its status as an enabler for HR analytics, especially integrating different data silos (e.g., Rasmussen and Ulrich, 2015), which could provide more evidence of the usefulness of HR analytics.

This scarcity of empirical evidence leads some authors to speculate that HR analytics might be considered a fad (Rasmussen and Ulrich, 2015; Angrave, Charlwood, Kirkpatrick, Lawrence, and Stuart, 2016), yet anecdotal evidence from practice suggest that HR analytics is gaining momentum in the everyday business. We suggest, that more evidence is needed to provide support to the notion that HR analytics is providing added value to the business (e.g., Rasmussen and Ulrich, 2015).

In this paper we focus on a special class of HR analytics and HR DSS, named strategic competence analytics for recruitment and selection. Exploring various issues in HR, such as recruitment and selection, defined as the "process of seeking applicants for potential employment" (Noe, Hollenbeck, Wright, and Gerhart, 2014, p. 762),

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might serve as a case for examining the additional positive effects and usefulness of HR analytics for business (Marler and Boudreau, 2017). When recruiting potential employees, it is important to know what the company is looking for in a new employee. The description of a competence helps, as it provides HR recruiters with a set of knowledge, skills, and abilities (KSA's) combined with personal characteristics to look for in potential employees. This competency describes important enablers for employees to fulfill their job (Noe, Hollenbeck, Wright, and Gerhart, 2014). Strategic competencies are competencies that the company must obtain, in order for them to fulfill their business strategy (Barney, 1991).

This research aims to provide a practical business case study example, which shows the potential of HR analytics and BDA in the HR function. In doing so we answer a call to provide more empirical evidence showing the business value of HR analytics on a recruitment case (van den Heuvel and Bondarouk, 2016; Marler and Boudreau, 2017, Batistič and Van der Laken, 2018). We base our case study on *knowledge hubs*, defined by Knight (2013) as a group of individuals that focus on "… the production and application of new knowledge which has the potential for commercial use". Knowledge hubs are characterized by high connectedness and high internal and external networking and knowledge sharing capabilities (Evers, 2008). Hubs have three major functions: producing knowledge, putting knowledge to practice, and passing on this knowledge through education and training. In HR, knowledge hubs could be used for more effective recruitment activities by analyzing both internal, (for example: employee's education, conferences visited, publications made) and external data (for example: graduates of a certain study, LinkedIn profiles regarding a business function), and then linking the internal and external data to model relationships between the enterprise and the knowledge hubs. Having this information, the HR department can decide on which knowledge hubs to focus their recruitment efforts and create an action plan. Our case study shows how to answer typical questions in competence analytics and derive related metrics, like:

- Where are knowledge hubs related to the company located?
- Which knowledge hubs are relevant for the company and what is the size of the relevant knowledge hubs?
- How close are the knowledge hubs to the company in terms of internal and external network analysis?

Our study has two important theoretical contributions. First, it provides further evidence of the usefulness of HR and competence analytics in a business environment and puts the emphasis on knowledge hubs in the recruitment and selection domain and provides a convenient practical model that organizations can use. In doing so, we also show how overcoming the limitations of the silo mentality, due to lack of HR IT infrastructure (Rasmussen and Ulrich, 2015) in place, and how a link between internal and external databases valuable for the recruitment process, further enhance the value of HR analytics (Brown and Vaughn, 2011. Second, we also contribute to the information systems (IS) literature by adapting existing models for strategic workforce planning from Phillips and Gully (2009) and Makarius and Srinivasan (2017) to data-driven competence analytics. We show the usefulness of this model in a case study at the ABC-company.

This paper is structured as follows. In Section 2, a model for data-driven competence analytics is presented. This model is used in a case study in Section 3, to identify important knowledge hubs in a company's network of related institutions and individuals. Finally, theoretical and practical conclusions are drawn.

2 STRATEGIC COMPETENCE ANALYTICS

2.1 Recruitment and Knowledge Hubs

Human Resource Management (HRM) refers to the "policies, practices, and systems that influence employees' behavior, attitudes, and performance" (Noe et al., 2014). The strategic objective of HRM is to maximize their positive influence on company performance. The recruitment and selection process is an integral part of HRM. We consider a potential employee's KSA's to be heavily related concepts that HR recruiters look for in this process. In HR literature (Marler and Boudreau, 2017), the importance of KSA's is stressed in the knowledge-based view of the firm, this view sees knowledge as the most important strategic resource of the firm for value creation.

Furthermore, social networks are important to knowledge, as they have been shown to have an influence on its creation, diffusion, absorption, and use (Phelps et al., 2012). Phelps et al. (2012) define a knowledge network or hub as "a set of nodes—individuals or higher-level collectives that serve as heterogeneously distributed repositories of knowledge and agents that search for, transmit, and create knowledge—interconnected by social relationships that enable and constrain nodes' efforts to acquire, transfer, and create knowledge". Knowledge hubs consist of nodes that represent actors within the network. These nodes represent individuals or collectives such as universities, research institutes, companies, and project teams. The knowledge hubs can become a source of a competitive advantage according to the knowledge-based view. This is confirmed by Vauterin et al. (2013), who mention that in highly competitive markets access to, and retainment of people and ideas is supported by strong social network relationships. Making these knowledge hubs a source of a competitive advantage and a structure to be exploited in recruitment and selection (Phelps et al. 2012).

2.2 Model for Data-driven Competence Analytics

Strategic workforce planning (SWP) is used by firms to "identify and address current and future challenges to gaining the right talent, in place at the right time" (Phillips and Gully, 2009). Acquiring and retaining talent is a necessity for successfully executing a firm's business strategy, and a strategic and proactive approach helps a firm to get the right talent. HR analytics can be used in SWP to assure accurate and real-time information in the planning process (Momin and Mishra, 2015). This gives firms an overhand on their competitors, which is necessary in highly competitive talent markets. The Talent Supply Chain Management (TSCM) model from Makarius and Srinivasan (2017) aims to align talent supply with talent demand by creating a relationship between the firms and talent suppliers such as universities, a topic which is missed in the SWP model. In order to tackle the problem of misalignment between knowledge supply and demand we adapt the SWP model for data-driven strategic competence analytics. In this adapted SWP* model, we fully integrate the strategic knowledge sourcing process derived from Makarius and Srinivasan (2017). Figure 2 in the Appendix provides an overview of the SWP* model.

In the SWP* model, a step related to the development of strategic competence data analytics and knowledge sourcing is added after Step 3 'Gap identification'. Step 4 'Strategic competence analytics' is composed out of sub steps 4a-4c:

- Development of a sourcing strategy (*step 4a*);
  - Analyze internal HR data to determine the skills expected of future employees.
  - Analyze internal and external data to identify knowledge hubs using social network analytics.
- Development of hub selection criteria (*step 4b*);
  - Determine a multi-criteria hub selection approach. For example, by using criteria like inter-hub competition for talent, long-term relationship potential, cost of creating tie, etc.
- Knowledge hub evaluation (*step 4c*).
  - Make a selection from the total number of knowledge hubs by using the most important criteria.

In summary, the 6-step SWP* model is an extended version of the 5-step SWP model Phillips and Gully (2009, with a dedicated step for strategic competence analytics after step 3 based on the TSCM model Makarius and Srinivasan (2017).

2.3 Social Network Analysis

To facilitate the identification of knowledge hubs in the sourcing strategy step (4a), social network analysis is integrated. This analysis comprises:

- *Data Collection and Preparation*: For the formation of knowledge networks, three classes of data sources are important:
  - *Internal data* from HR information systems: e.g. employee IS, performance management IS, recruitment IS, etc.
  - *Professional Social Networks*: e.g. LinkedIn (2019), Xing (2019), etc.
  - *Scientometric* and *Bibliometric Databases*: e.g. Web of Science (2019), Scopus (2019), Patstat (2019), Research Gate (2019), etc.

  These data sources are integrated in the data preparation phase, on the level of individuals and organizations, and fed into a dedicated data mart for HR and competence analytics.
- *Knowledge Hub Visualization*: With the HR data mart we connect software for competence analytics and knowledge hub visualization. Two types of software are relevant: 1) software for performance dashboarding (e.g. MS Power BI (2019)) and 2) software for network visualizations and analysis (e.g. Gephi (2019)). With 1) HR professionals create interactive visualizations and overall competence measures and geographic HR data, and with 2) knowledge hubs are visualized and analyzed.
- *Knowledge Hub Analysis*: In this analysis, we first determine community structures within the complete network, indicating structures of competence, institutes or individuals, with the algorithm described in (Blondel et al., 2008). This

algorithm reports the network modularity, where a high score represents a network with dense connections. Network nodes have a certain position within a knowledge hub (Phelps et al., 2012). Therefore, another prospective way of creating ties between hubs is the targeting of such specific persons in the hub that have a central position. These people can be used as an influential link to other players within their hub, thereby creating a connection from hub to hub. Central individuals are recognized by using typical centrality measures as: closeness, betweenness, and degree centrality (Sumith et al., 2017). Ties between actors are viewed as a means through which information and know-ledge are transferred. Direct ties are perceived to be more efficient for sharing relevant and complex information, compared to indirect ties (Singh, 2005). An individuals' central position within a network allows them to have more up-to-date access to rich and diverse information, which increases their ability to gain knowledge from their network (Phelps et al., 2012). Therefore, individuals or institutes with a higher value for the centrality measures, compared to others, are perceived to be more knowledgeable actors in a knowledge network. Especially degree centrality, which measures the number of direct ties, is important in determining knowledgeable nodes in a network (Zhang and Ma, 2016). Besides, the centrality measures are used to cross-validate an actors' importance. Network eccentricity is used to determine the distance a certain node will have to travel to the node furthest away from it. This measure is used to benchmark how far the company is from other nodes.

3 CASE STUDY ON STRATEGIC COMPETENCE ANALYTICS

3.1 ABC-company's Supply and Demand Profile

This case study focuses on one of the technical competencies identified within the ABC-company, a large technical multinational based in The Netherlands. The name of the company is anonymized here because of rules related to non-disclosure. The ABC-company delivers state-of-the-art technology in its field. ABC has a business strategy that aims to achieve technological leadership with an operational excellence and customer focus. Innovation in all business segments is very important. The company's talent strategy starts by identifying its core competencies. This was done through strategic competence sourcing. A competency is identified as a critical core competency when:

1. There is long-term demand for the competence.
2. There is high demand for the competence.
3. There is low availability of the competence in the external labour market.

The criticality of these competencies has been determined by looking at projected growth of demand, and the time needed to hire a person within the specific competency. This has led to the identification of core competencies. This case study focuses on one of these: *competence X*. Competence X is the competency in the ABC-company for which demand is expected to grow the most of all competencies for the years to come, and the talent for competence X is needed in several of its branches.

Competence X is an area of knowledge for which the ABC-company's demand in the long-term is high, but the supply from the labour market is low. Analysis shows that a several hundreds of additional functions related to competence X are expected to open this year. The current de-mand for competence X in the global market is around 6,000 in 7 significant countries identified by (Gartner, 2019): The Netherlands, South-Korea, Japan, China, India, Germany, and Israel. In terms of demand, the company has a need for potential employees with a master's degree or a PhD. Talent supply in the same nine countries as identified before by Gartner (2019) offer a supply of around 35,000 competence X talents. Currently the gap between demand and supply is mainly experienced for master-level competence X employees. However, it is predicted that the overall gap for both master and PhD students will grow in the future. Therefore, it is important to start recruitment efforts in knowledge hubs.

3.2 Data Collection and Preparation

In order to map the ABC-company's internal knowledge network for competence X, a data set is created, described in Table 1. The dataset covers 124 employees, 136 of their co-authors, and their 127 knowledge products written in the last 20 years.

Four sources of data are identified, listed in order of importance:

1. Internal data obtained from the ABC-company's records. This data has been anonymized by replacing employee numbers by identification numbers. Age has been grouped within intervals.

Table 1: Data entities for the internal knowledge hub.

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="3">Data Entity</td></tr>
<tr><td>Employee data</td><td>Knowledge Products</td><td>Co-Author data</td></tr>
<tr><td rowspan="10">Data Source</td><td rowspan="4">ABC company</td><td>Nationality</td><td rowspan="4"></td><td rowspan="4">Employee Number</td></tr>
<tr><td>Country of Employment</td></tr>
<tr><td>Age Group</td></tr>
<tr><td>Gender</td></tr>
<tr><td rowspan="2">LinkedIn and Xing</td><td>Education (Institute, Study, Level, Location) (1969- 2018)</td><td rowspan="2"></td><td rowspan="2"></td></tr>
<tr><td>Working Experience (Institute, Length, Function, Location) (1988-2018)</td></tr>
<tr><td rowspan="4">LinkedIn, Research Gate, Xing</td><td rowspan="4">Skills</td><td>Product Type (Journal Article, Patent, Report, or Conference)</td><td>Name</td></tr>
<tr><td>Title</td><td>Current Employer(s)</td></tr>
<tr><td>Source</td><td>Country of Employment</td></tr>
<tr><td>Date of Publication (1999 to 2018)</td><td>Skills</td></tr>
</table>

2. LinkedIn. LinkedIn is an online social network used for professional networking, including job and CV posting. Data has been obtained through the recruitment tool offered by LinkedIn, namely LinkedIn Recruiter. With over 530 million members worldwide, it offers a wide base of labour market data (LinkedIn, 2019).
3. Research Gate. Research Gate is a social networking platform where scientists and researchers share papers, ask and answer questions, and find collaborators. It has over 15 million verified scientist members (ResearchGate, 2019).
4. Xing. Xing is a social networking site targeted at professionals in German speaking countries Germany, Austria, and Switzerland. In these countries, Xing has over 13 million users (Xing, 2019).

Two different types of individuals were identified, each with their own sourcing method:

1. Employees were identified through the competence X employee list obtained from internal company records.
2. Co-Authors were identified by gathering the names of co-authors or co-owners belonging to articles and patents written or owned by the ABC-company's personnel.

Knowledge products like journal articles, patents, reports and conference publications serve as a link between these two types of individuals; together creating ABC's internal knowledge network. The obtained data was then accumulated in the HR data mart and imported into the analytics software to create visualizations.

3.3 Sourcing Strategy

The sourcing strategy consists of the following components:

- the analysis of internal HR data to determine the skills expected of future employees.
- the analysis of both internal and external data to identify knowledge hubs.

Map visualizations are used to answer questions Q1 and Q2:

Q1. "*Where are the competence X's knowledge hubs related to the ABC-company located?*", and
Q2. "*Where are the external competence X's knowledge hubs located worldwide?*".

Question 1 is answered by comparing the geographical maps produced by the analytics software. These show the location of employees' current and past employers, location of current employers of the co-authors, and location of the employees' past educational institutes, respectively. Looking at the map, we can see the areas around the ABC-company locations are most heavily covered by related knowledge players in their hub. Especially Eindhoven, in the overall Europe area and the areas around San Diego and San Jose in America.

The co-author employer locations, depicted in Figure 1, show an interesting overview, suggesting additional locations such as: Israel, United-Kingdom, India, Turkey, China, Russia, Germany and Greece as possibly interesting knowledge locations. The Netherlands and East- and West-Coast of the United States remain large suppliers of knowledge players.

Question 2 is answered in the same manner. Here maps are used to show the location of external competence X talents' current and past employers, and the location of the external's past educational institutes, respectively.

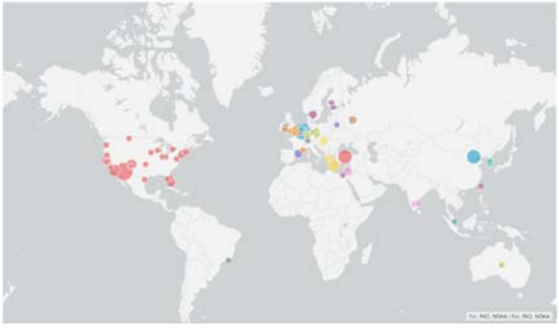

Figure 1: This map shows the locations of the current and past employers of the ABC employees' co-authors. The color of the labels indicates the country it is part of, the size of the labels indicates the number of co-authors that have worked for that employer.

3.4 Hub Selection Criteria

In order to select the hubs most relevant to ABC, a multi-criteria hub selection approach has been formulated based on the requirements of ABC. The requirements are the result of structured interviews with HR professionals. The knowledge hubs of interest are selected based on the following selection criteria, listed in order of importance to ABC:

1. The *occurrence of skills requested*. These skills ensure that the individuals in the hub, when selected or recruited, fulfil the different aspects of their job.
2. The *number of central actors*, based on the centrality measures: degree, betweenness, and closeness. The centrality of actors within a hub gives an indication of their knowledge base. Furthermore, the more connections an actor has, the bigger its impact will be when it is added to the internal network of ABC.
3. The *size of the hub*. The size of the hub is based on the number of actors that are part of the hub. The larger the number of actors, the more interesting the hub will be. Any recruitment activities will be able to yield a larger number of possible employees.
4. *The competition for individuals in the hub*. This selection criterion is applied on the hubs that remain after the first three criteria. Gartner's TalentNeuron (2019), a platform used by ABC providing talent analytics insights, is used to gain information on the competition for competence X talent in the geographical areas of the selected hubs. When competition is high, it will be more difficult for ABC to recruit from these hubs.

Other possible selection criteria are based on the proximity to current locations of ABC, and the existence of connections to ABC:

5. *The proximity to actual locations of ABC branches* is currently not an important selection criterion to ABC. ABC has specified that it is willing to open branches in new locations, if the size of the talent supply there gives them reason to.
6. The *existence of direct connections to ABC* is currently not an important selection criterion to ABC. Already having a connection to important hubs will make it easier to approach them for recruitment. However, it is more important to get insight in all hubs that could be of interest to ABC, not just the ones where ABC already has some kind of relationship with.

3.5 Internal Network Analysis

Figure 3 in the Appendix depicts the internal network for competence X. The centrality measures allow us to identify the most 'knowledgeable actors' in its network. Table 2 gives an overview of the ten most important institutions and their centrality measures, ordered by degree, and Table 3 gives an overview of the ten most important individuals and their centrality measures, again ordered by degree.

Table 2: Top-10 centrality measures for internal network institutions.

Institute	**Centrality measure**		
	Degree	***Betweenness***	***Closeness***
Eindhoven Univ. of Technology	20	0.011904	0.325911
University of Arizona	16	0.007337	0.310212
Tech. company XYZ	11	0.002154	0.312621
University of Twente	10	0.001427	0.304348
Delft University of Technology	9	0.001763	0.312621
Utrecht University	7	0.003895	0.315068
TMC	7	0.001033	0.306667
Imperial College London	6	0.005639	0.346237
University of Groningen	6	0.000558	0.297048
Hellas (FORTH)	6	0.000168	0.26094

Table 3: Top-10 centrality measures for individual actors.

Individual	Centrality measure		
	Degree	*Betweenness*	*Closeness*
Employee 4051	41	0.413872	0.509494
Co-Author 34	19	0.003991	0.350763
Employee 4111	16	0.015800	0.431635
Employee 4117	15	0.012473	0.428191
Employee 4112	12	0.011973	0.427056
Co-Author 44	12	0.001183	0.346237
Co-Author 38	12	0.000896	0.346237
Employee 4115	10	0.005898	0.423684
Co-Author 40	10	0.002686	0.345494
Co-Author 42	10	0.000632	0.345494

The ten most important individuals have been selected based firstly on their degree centrality, as direct relationships have been assumed to contribute most to an actor's knowledge (Phelps et al., 2012). The betweenness and closeness centrality measures have been normalized, which makes it easier to see the difference between actors.

Inspecting Table 2, we see institutions that are important according to all centrality measures, the top-3 being: Eindhoven University of Technology, University of Arizona, and Tech. company XYZ. Looking at the most important individuals in the network depicted in Table 3, we see Employee 4051 and 4111 in the top-3 based on all centrality measures, and Co-Author 34 based on degree centrality. These institutions and individual actors play an important role in ABC's knowledge network, and since these are all part of ABC's internal network, the relationships of this network are used in approaching the institutions and individuals connected to them in the external network.

The identified institutions can be associated with via partnerships and the universities might be partnered with to secure future supply of talent. The companies are important to ABC for the purpose of knowledge sharing. All institutions are candidates for recognizing suitable employees in the selection process, when they occur in an applicant's curriculum vitae. In the future, the data on the identified individuals of a network is used to create an average persona to which future candidates can be compared in the selection process. Furthermore, the recognition of central individuals in the network of a strategic competence makes it easier to recognize whom to turn to when questions regarding this competence arise. Since degree centrality is a measure of direct connections, and with that an indicator of knowledge, it suggests that, although Co-Author 34 might not hold much knowledge of competence X on its own, this person is able to refer to the right people and can create a team of knowledgeable actors.

3.6 Knowledge Hub Evaluation & Recommendations

Using the concept of network modularity, 38 hubs or sub-networks are detected in the network for competence X. The modularity score of the competence X network is high with 0.846, indicating strong community structure within the network. In order to answer the question: "*Which of these knowledge hubs are relevant to ABC?*" we apply the selection criteria identified in coordination with ABC to the 38 identified hubs. Selection criterion one, *the occurrence of demanded skills*, has been met through the data collection method. The externals' skills are, like the employees and co-author's skills, directly related to the demanded skills. The internal ABC network has been confirmed to contain skills that are related to the skills demanded by ABC. The external network consists of individuals that have at least ten of these skills. Therefore, all 38 hubs satisfy the first selection criterion.

Selection criterion two, *the number of central actors*, evaluates the 38 remaining hubs according to their number of central actors. The actors are deemed 'central' when at least two centrality measures identify them to be among the ten most central individuals or institutes. In the competence X network analysis, for example, the 'Eindhoven University of Technology'-hub is evaluated as a central institute and Employee 4051 is evaluated as a central individual. The remaining hubs are then evaluated according to their *size expressed in number of actors*. This analysis indicates, for example, that the 'Eindhoven University of Technology'-hub and the 'Indian Institute of Technology'-hub are relatively large in terms of size. Lastly, we determine *competition for talent* in the locations of the central actors of these five hubs. We use TalentNeuron (Gartner, 2019) to determine the demand for competence X personnel in the locations of these hubs. After this analysis several hubs are excluded because the number of direct employers competing is very high. This last selection criterion leaves, for example, Eindhoven and Kanpur as most desirable hubs after applying the SWP* model.

In order to answer the question: "*How close are these knowledge hubs to ABC?*", we define the metric *weighted number of ties (*WNT). This metric counts the number of ties from ABC with the resulting hubs from the hub selection process. The WNT is defined as the weighted total of: 1) the # of ABC employees belonging to that hub (w_1=1), 2) the # of institutes ABC has a partnership with (w_2=1), and 3) the co-authors of ABC employees (w_3=0.5). The co-authors have a smaller weight, since these actors are often not directly connected to ABC. The WNT determines the approach of action that has to be taken towards the hub. A low WNT indicates that the first step should be creating partnerships and creating awareness of ABC within the hub. A high WNT indicates a relationship exists already, therefore these can be used to source knowledge talent from these hubs. In this case the 'Eindhoven University of Technology'-hub has a high WNT close to 50. Next, we connect the hubs with a high WNT to the identified central actors. For these hubs and actors, the recruitment actions are, for instance: to build a 'persona' based on data on the individuals within the hub that recruitment will be targeted towards, and to build partnerships/relationships with central institutions and individuals. And as a final step, it is important to continuously monitor the strategic competence network, and evaluate the selection and recruitment activities' positive and negative effects per hub. By doing this, up-to-date network information is ensured, and the recruitment and selection activities are fine-tuned to the specific hubs.

4 CONCLUSIONS

4.1 Theoretical Contribution

By providing a case study of the usage of analytics in knowledge hubs related to the recruitment and selection process, we provide two main theoretical contributions. First, we provide much needed empirical evidence on how the right usage of HR analytics can have beneficial effects on the organization business (Marler and Boudreau, 2017) and especially in the recruitment and selection domain of the HR function. We provide an example on how HR decision making benefits by triangulating internal and external data (Brown and Vaughn, 2011), and show how beneficial it is for the HR function to overcome its internal focus and look for useful data even outside the function itself (Rasmussen and Ulrich, 2015). The proposed model SWP* contributes to the literature by providing an example on how the use of strategic competence analytics and overall HR analytics, helps the organization recognize and utilize competencies in and around the firm. For example, the results and proposed model show, how recruiters identify important talents or important institutions in their knowledge network, which in the end provide the organization with unique human capital – as they can focus to recruit specific individuals with unique SKA's (Lepak and Snell, 1999). Second, we also contribute to the general IS literature by further developing a model for data-driven competence analytics, inspired by the work of Phillips and Gully (2009) and Makarius and Srinivasan (2017), in producing and validating dedicated analytics for HR. In the model, knowledge hubs are identified algorithmically as community structures and subsequently analysed with centrality measures. Hence, concepts from network analysis are applied in the context of strategic competence analytics. In addition, the presented method builds also on the visualization strength of network analysis, which provides a simple and effective overview of the most important actors in the knowledge hub. This approach enables recruiters to identify hubs that fulfil their criteria of interest, recognize the important players in these hubs, identify their connections to these hubs of interest, and adapt their recruitment strategy accordingly.

4.2 Practical Implication

Instead of relying purely on social capital and intuition to find the right talents, recruiters, can use the model provided in this paper. The model provides an easy to understand network visualization, which potentially points out individuals and institutions that have a strong connection with the company. Such networks provide data-based insights into central actors within the company network, which can be targeted for recruitment.

4.3 Limitations and Future Work

A limitation of this paper is the fact that only a confined number of data sources has been used as sources for the network data. For example, LinkedIn has high coverage of the labour market of the USA, but low coverage of the East-Asian and African labour market (LinkedIn, 2019). Therefore, the representation of population by the data is not entirely accurate. Future research should include multiple sources of data to obtain more reliable and global results, such as Facebook (Brown and Vaughn, 2011). In addition, for future research we want to:

- Develop appropriate models for data cleaning,

to better facilitate the integration of HR data sources and align with legal issues.
- Finetune the set of relevant metrics for competence analytics, and
- Validate and develop the presented model at more companies and organizations.

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APPENDIX

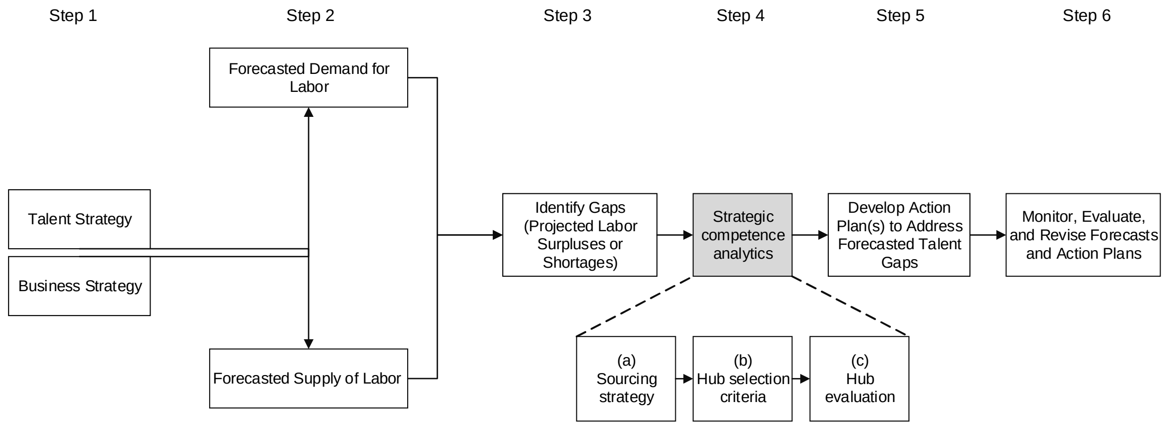

Figure 2: Model for data-driven strategic competence analytics (SWP*). Adapted from Phillips and Gully (2009).

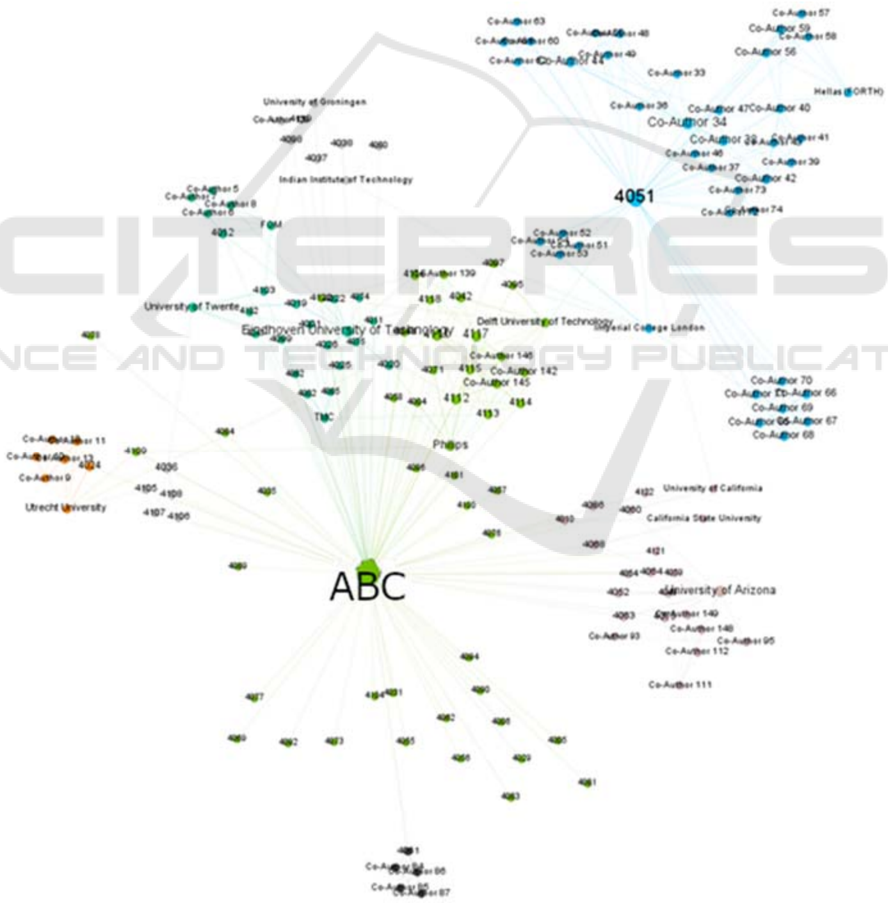

Figure 3: This knowledge network shows the internal network of ABC. The size of the nodes is determined by degree centrality, and its color by the modularity class. Nodes with a low degree centrality are filtered out to improve visibility of important actors.