What Really Counts - An Exploratory Study of the Impact of Aggregated Data on Person Perception

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ABSTRACT

Aggregated data have been used in human resource management to reduce a number of data into small pieces of information. Their use is aimed at supporting decision-making. However, less is known about the impact of aggregated data on person perception, which is decisive in, for instance, recruitment. With reference to warranting theory (Walther & Parks, 2002), we assume that aggregated data in the form of different indices on a business networking site have the power to affect the impressions of employability and destructive leadership behavior. To examine the impact, we conducted a 2 (low vs. high number of commonalities) × 2 (low vs. high number of contacts) × 2 (low vs. high activity level) × 2 (male vs. female) between-subject online experiment (N = 665). The analyses showed no direct effects of the indices on person perception; however, there were significant interaction effects with the profile proprietor's sex. Results indicate that aggregated data can support decision-making and can promote equality between female and male job candidates.

Key Words: Aggregated data, warranting principle, business network sites, recruitment: gender equality

1 Introduction

Automatically generated information has become an important issue in information systems, for instance, in the form of data mining. Data mining provides the opportunity to aggregate a large number of data resulting in small pieces of information that can be processed by users more easily and supports decision-making (Speier & Morris, 2003). For this reason, data mining is also a trend in human resources management (HRM; Strohmeier & Piazza, 2013). Another trend in HRM is recruitment via social media. Companies promote themselves on Facebook and Twitter, and distribute open positions in large repositories such as Monster or Stepstone. Business networking sites (BNS) such as XING and LinkedIn have become an essential part of the recruitment process for employees and employers alike (Weitzel et al., 2017). BNS also use aggregated data to reduce information for their users (e.g., reducing a detailed contact list into a simple number of contacts) allowing for faster profile screening. However, Strohmeier and Piazza (2013) report that little is known about how these reductions into single cues affect decision-making in HRM. In this context, warranting theory (Walther & Parks, 2002) claims that the more a piece of information is resistant to manipulation the higher is its warranting value (DeAndrea, 2014) in terms of credibility. Based on a cue's credibility further impressions of a target person can be drawn. Assuming, that aggregated information is largely immune to manipulation in contrast to self-generated information, such as indication of vocational competencies, it should be quite powerful for impression formation. Research on social media has provided the first insights into the impact of single aggregated pieces of information on social attractiveness.

The most often examined aggregated information is the number of friends. Tong, Van Der Heide, Langwell, and Walther (2008) have shown that a moderate number of friends elicits the highest ratings in credibility and social attractiveness, while a low number and a very high number lead to decreased ratings. Compared with research on, for instance, Facebook, BNS provide a professional setting in which other variables are more decisive. It is less about being socially attractive (e.g., in terms of friendships) than about being employable and having professional competencies such as leadership qualities or communicative competence (McEvoy et al., 2005). It seems that there is an even greater need for a beneficial impression in the professional context (e.g., when looking for a job), than in the private context (e.g., adding another friend). However, a key point is that the user is less capable of controlling the aggregated data, because the system and the algorithms created by the system engineers determine which data are aggregated and how they are represented. Therefore, we want to take a step back from procedures of data mining and examine the power of single aggregated information on business-related attributions. Firstly, the results can extend our theoretical knowledge (and scope) of warranting theory (e.g., examined dimensions, professional context) and HRM (e.g., how do aggregated data affect perception of an employer?). Secondly, our study can have practical consequences on recruiting processes (e.g., using aggregated data or not) and on decisions of which data should be aggregated

and how (e.g., responsibility of system engineers). In the following, we describe candidate screening on social media and explain the fundamental processes of person perception. We then outline warranting theory and present our hypotheses. Finally, we provide an exploratory section, which examines the potential power of aggregated data to achieve more gender equality in the business sector.

1.1 Candidate Screening via Social Network Sites

Networks such as XING, LinkedIn, Facebook, and Twitter are among the most important channels for companies for candidate searching, employer branding, posting open positions, and finding more information about a candidate (Bizer et al., 2005; Brown & Vaughn, 2011; Weitzel et al., 2017). It has become fairly common for organizations and their human resource (HR) managers to effectively recruit and screen potential job candidates via social networking sites (SNS; Chiang & Suen, 2015; Davison, Maraist, & Bing, 2011; Vicknair, Elkersh, Yancey, & Budden, 2010). While SNS like Facebook are used particularly for private reasons and provide a lot of (technical) opportunities for self-presentation (Papacharissi, 2009), BNS have also been described as "Facebook in a suit" (Van Dijck, 2013, p. 208) emphasizing the professional background of the user. Accordingly, BNS are also SNS, but with a professional scope. Users can provide information on their career, their current job position, their education, their competencies, what they are professionally looking for, personal statements, hobbies, and interests. They can join interest groups and group discussions.

Recruitment agencies use these profiles to screen potential job candidates (Ollington, Gibb, & Harcourt, 2013). "[T]he recruiter acts like a broker in a 'hub-n-spoke' structure, occupying a centralised position between job seekers and employer(s)" (Ollington et al., 2013, p. 250) always looking for the fit between employee and employer (Kristof-Brown, 2000), which crucially includes seeking for critical information about the candidate (Ollington et al., 2013). Seeking information on SNS presents recruiters with the challenge of filtering the amount of information and figuring out which information is credible to draw a reliable impression of a job candidate.

Carr, Hall, Mason, and Varney (2017) specify that employers strive for uncertainty reduction in potential job candidates regarding the candidate's knowledge, skills, and abilities so as to predict their success and occupational behavior and to reach a decision on the candidate's employability. The amount and type of information can affect the evaluation of a job candidate (Carr, 2016). For instance, job candidates who present more positive information about themselves are judged as more employable and competent (Carr & Walther, 2014).

Recruiters look at diverse elements of a professional profile to gain an impression of the job candidate, the most important ones being the number of connections, the current employer, and personal information (Zide, Elman, & Shahani-Denning, 2014). Although one may argue that recruiters are experienced in categorizing professional data and avoiding bias, different studies in the offline HRM context revealed that their judgments are very similar to those of inexperienced persons such as students (Jansen, König, Stadelmann, & Kleinmann, in press; Ruetzler, Taylor, Reynolds & Baker, 2011; Ruetzler, Taylor, Reynolds, Baker & Killen, 2012; Posner, 1981; Wood, Schmidtke, & Decker, 2007; Zhao, 2006). Notably, there are small differences, for instance, in the evaluation of the reputation of an applicant's university (Zhao, 2006), which inexperienced persons might overlook. However, the fact that both groups rely on social categories, for example, appearance, clothes, sex (Ruetzler et al., 2012; Zhao, 2006), is in line with research about fundamental person perception. Bargh and Chartrand (1999) revealed that person perception processes tend to be automatic, because the sparse cognitive capacities to process information in a controlled way are needed for other decisions and actions.

Overcoming this automaticity requires a lot of cognitive energy (Devine, 1989). Every time a person uses automatic processes, he/she refers to deeply rooted cognitive structures (stereotypes), which then act as heuristics – mental shortcuts. In this case, individuals, especially cognitively strained individuals, base their impression on single information, which is easily available. One of the strongest cues here is someone's sex category, involving the assumption that men are assertive and act in an agentic way, while women are loving and act in a communal manner (e.g., Prentice & Carranza, 2002).

This process facilitates the connection of new information with old information and allows one to work efficiently. For example, recruiters or HR managers can draw on automated processes and stereotypical beliefs about single social cues of applicants being able to work in an effective way during stressful day-to-day work. Referring to automaticity, it seems even more important to examine the impact of (uncontrolled) aggregated cues, which are aimed at decision-making support.

1.2 Aggregated Data and Their Information Value

Warranting theory aims to explain why some information in the online context is more credible than other information, assuming that only credible data are valuable data (Walther & Parks, 2002). Based on the credibility of information, its warranting value, further impressions of a target person can be drawn. Park (2011) concluded that the power of online information in terms of its warranting value increases when it is available in a public channel because others can confirm or disprove one's self-presentation. "The warranting value of information reflects a perception about the extent to which information is immune to manipulation by the person or entity that it describes" (DeAndrea, van der Heide, & Easley, 2014, p. 63).

Reflecting a broad body of research, DeAndrea (2014) summarizes three types of information affecting person perception on SNS: (1) self-generated information (e.g., profile picture, job history, educational information); (2) other-generated information (e.g., reactions to posts by commentators); and (3) system-aggregated information

(meta information like number of contacts, activity index). Most research referring to warranting theory has been conducted on the impact of self-generated data (e.g., how does a certain type of picture affect person perception?) on impression formation, and secondly on other-generated information (e.g., how do a certain number of comments of friends, influence person perception?), while it has rarely been demonstrated how aggregated data affect person perception (see DeAndrea, 2014).

Control or the possibility of modification plays a decisive role in warranting theory because "the less information is perceived to be controllable by the person to whom it refers, the more weight it will carry in shaping impressions" (DeAndrea, 2014, p. 5).

Users naturally control which (1) self-generated data in the form of pictures or texts they post on their SNS profile; they are free to manipulate this information to create a beneficial impression of themselves (e.g., using filters in pictures or writing how successful, warm-hearted, or altruistic they are). As a result, the warranting value of this information for impression formation is rather low (Walther & Jang, 2012).

By contrast, less access for modification is given regarding (2) other-generated or (3) system-aggregated information that may lead to an extraordinary warranting value of this information (Walther & Jang, 2012). Limited, but possible, access for manipulation is given regarding other-generated information. Users, for instance, can ask their friends to make positive comments about their new profile picture, or worse, pay professionals to write positive comments, which can be observed in the context of online purchases (e.g., fake product recommendations). Research has shown that other-generated information can affect the perceiver's impression of social attractiveness (Antheunis & Schouten, 2011) and professionalism (Carr & Stefaniak, 2012). In a more recent study, Carr et al. (2017) demonstrated that other-generated information in the form of job performance evaluation and further recommendation is more decisive for impression formation than self-generated information, such as describing one's own abilities.

The possibility to modify system-aggregated data is even less given, because it widely depends on third parties in the background who set the rules for the implemented algorithms. On the one hand, reducing a certain amount of information into single cues means reducing the quality of information. On the other hand, it can support decision-making since it minimizes cognitive effort to process the information. Moreover, these few cues in turn can function as cognitive heuristics that decisively direct person perception, especially when individuals are cognitively exhausted (for more details, see Van Der Heide & Schumaker, 2013, Walther & Jang, 2012, and Westerman, Spence, & Van Der Heide, 2014).

Owing to the assumed power of aggregated data, it seems reasonable to extend research by examining the effects of aggregated data in the HRM context, in which such data have already been used (e.g., Chien & Chen, 2008; Lee & Tseng, 2018; Madni, Anwar, & Shah, 2017; Shehu & Besimi, 2018).

Today, research on *warranting theory* predominantly deals with the impressions of social attractiveness in privately used SNS (e.g., Utz, 2010; Walther, Van Der Heide, Hamel, & Shulman, 2009). However, to refine the theory and determine its scope of application, more empirical research is needed that focuses on other dimensions of impression formations. HRM in the context of BNS appears to represent a suitable and authentic setting to test for other dimensions of impression formations. Initial efforts in this direction were made by Carr et al. (2017), who focused on the employability of job candidates or by Schouten, Antheunis, Abeele, and Van Lith (2015), who investigated the impact of credible information on personality traits, such as consciousness. However, the aforementioned research refers to self- and other-generated information and neglects the impact of aggregated data. Considering that aggregated data are used in the HRM context (Strohmeier & Piazza, 2013), it seems reasonable to focus on job-relevant dimensions, such as employability or professional competencies (Almalis, Tsihrintzis, & Karagiannis, 2014; Heijde & Van Der Heijden, 2006; Khorami, & Ehsani, 2015; Li, Lai, & Kao, 2008; Liu et al., 2016; Nilsson & Ellström, 2012; Strohmeier & Piazza, 2013). Among these professional competencies are leadership qualities (McEvoy et al., 2005). While research on leadership styles has focused on the positive preconditions and consequences of leading (e.g., transformational style, charismatic leaders, see Schyns & Schilling, 2013), it currently also emphasizes the destructive side of leadership, because of the disastrous consequences for companies. Destructive leadership implies destructive behavior directed at subordinates (e.g., invading subordinates' privacy) and includes malevolent behavior against the organization (e.g., stealing company property and resources); companies should strive to avoid hiring such leaders (for a detailed review, see meta-analyses by Schyns & Schilling, 2013).

Therefore, we want to examine whether and to which extent aggregated data are capable of affecting person perception in terms of destructive leadership and employability in the HRM context. Carr et al. (2017) have already demonstrated that employability is affected by self- and other-generated information; however, the impact of aggregated data was not examined.

First, our study extends warranting theory concerning the power of aggregated data and affected dimensions of impression formation. Second, this information is valuable for practitioners to ensure that aggregated data support their decision-making processes in viable ways.

1.3 Aggregated Data in BNS

Aggregated data are used in HRM to reduce the amount of information HR managers or recruiters have to process and to facilitate decision-making (e.g., Chien & Chen, 2008; Lee & Tseng, 2018; Madni et al., 2017). Such information is also provided on BNS, which are increasingly used to recruit employees, in different ways. The BNS XING generates scores about the profile's proprietor, which are available for every logged in user. These scores are presented right next to the proprietor's profile picture and current job status (see Figure 1). Scores refer to the commonalities with the user observing the profile, the number of contacts, and the activity in the network. We will consecutively present the three indices and derive our hypotheses. The more objective a source of information, the more power it should possess for impression formation (DeAndrea et al., 2014). Therefore, aggregated data might be very powerful. However, these data can still be modified to a certain extent by, for instance, sending out numerous friend requests. Because these requests are not necessarily accepted, however, the manipulation is limited.

This means that there might be subtle differences in third-party information that can affect impressions (DeAndrea et al., 2014). For instance, a system that inhibits modification of third-party information by its users should be perceived as more trustworthy and valuable for impression formation (DeAndrea et al., 2014). In this respect, it is possible that the impact of aggregated pieces of information differs in the power for impression formation.

The *commonality score* indicates the number of commonalities the profile's proprietor (person A) shares with the person who is currently visiting the profile (person B). There is no comparable index in other SNS. This score is out of the control of the user, since the score depends on the current observer of the profile. The profile proprietor cannot adapt his/her profile for every potential observer. Therefore, referring to warranting theory, this score should have substantial power to influence impression formation. The commonality score can function as a similarity index. Byrne and Nelson (1965) state that, "... the attraction of a subject toward a stranger is a function of the similarity or dissimilarity of the latter's attitudes and values to those of the subject" (p. 659). Moreover, Byrne and Rhamey (1965) describe the law of attraction stating that increasing similarity leads to more familiarity and attraction in a linear function. Since then, the impact of similarity or commonalities have been validated for several contexts. The effect applies for actual and perceived similarity, for similarities in personality traits, leisure activities, and physical attributes (for a meta-review, see Montoya, Horton, & Kirchner, 2008) and represents a fundamental and strong process in person perception. Several studies in the HR context have revealed a preference of decision-makers for job applicants who show some similarity to them (e.g., Gallois, Callan, & Palmer, 1992; García, Posthuma, & Colella, 2008). Rivera (2012) focusing on intercultural recruitment, for example, revealed that candidate evaluation is driven by cultural similarities, leading to a preference for candidates sharing the company's cultural background.

To our knowledge, the perception of aggregated data in terms of a similarity or commonality index has not been investigated to date. We assume that the higher the commonality score, the more benevolent attributions will be made because it is a very basic but powerful effect driving person perception. As a consequence, a high number of commonalities might be associated with higher ratings of employability:

H1: A high number of commonalities leads to higher ratings on employability than does a low number of commonalities.

This might also apply for leadership evaluation. The impression of commonalities can make it more likely to attribute more favorable characteristics to a person appearing similar than to someone who seems to be less similar:

H2: A high number of commonalities leads to lower ratings on destructive leadership behavior than does a low number of commonalities.

The *contact score* shows how many business contacts the person has; it is comparable to the number of friends on Facebook or number of followers on Twitter or Instagram. Although the score comprises aggregated data, we assume that it can be partly modified by the user because the user can make efforts to increase his/her number of contacts or delete contacts. However, it is still made up of aggregated data, which neglects the quality of contacts. Consequently, regarding warranting theory, this index should still affect impression formation, but could have less power than the commonality index.

Forret and Dougherty (2004) report that intensive offline networking is associated with a higher probability of re-employment. In the BNS context, the *number of contacts* might indicate the social and/or occupational attractiveness of the depicted individual, since the more contacts a proprietor has the more attractive she/he might be, as, for instance, Antheunis and Schouten (2011) and Utz (2010) have shown for Facebook profiles. However, exceeding a certain number of contacts could be judged as inauthentic or socially unattractive, as Tong et al. (2008) demonstrated for Facebook. They found a curvilinear relation: While a low number (102 friends) as well as an extraordinary high number of contacts (902 friends) were socially unattractive, a moderate number (302 friends) was most desirable. Comparable empirical evidence for BNS is not available to our knowledge. Only few studies have investigated the role of contacts in BNS profile evaluation. Zide et al. (2014) revealed that the number of contacts is an important cue for recruiters on BNS; they did, however, not capture which inferences are actually made by profile viewers. Although it is not unequivocally

clear whether results referring to a concrete number of contacts from research on Facebook can be strictly transferred to BNS and which dimensions of impression formation they trigger, findings point in favor of a moderate number of contacts (e.g., Tong et al., 2008; Zide et al. 2014) for desirable impression formation. We assume the following hypothesis:

H3: A moderate number of contacts leads to higher ratings on employability in contrast to a small number.

Moreover, we suggest that the number of contacts could also affect perceived leadership qualities. It is important for leaders to gain and cultivate social contacts (Mehra, Dixon, Brass, & Robertson, 2006). A pyramidal workforce structure (few leaders, high number of subordinates; Jung, 2011) allows leaders to refer to a high number of potential contacts, because they refer to all their subordinates and their peers. By contrast, a subordinate would more likely refer to his/her peers. Such top–down structure allows leaders to refer to a high number of potential contacts; it is conceivable that leaders have larger networks and more business contacts than subordinates do. Furthermore, a strong communication ability is a characteristic that is attributed to a good leader (Barrett, 2006). If a moderate contact number represents this ability, this could result in lower ratings on destructive leadership behavior. Thus, we state the following hypothesis:

H4: A moderate number of contacts leads to lower ratings on destructive leadership behavior than does a low number of contacts.

The *activity score* refers to the intensity of activity (e.g., updating one's own profile, looking for new contacts, and writing messages to other users) and has no direct counterpart on, for instance, Facebook. In the broadest sense it may be comparable to the number of postings on Twitter or Instagram; however, the activity index refers to more actions than merely posting something. This score seems to have the most controllability by the user, because the user can strive for an increase of activity by updating his/her data or posting something. However, it is still out of the user's control which actions are actually included to aggregate this score. Considering warranting theory, we assume that in contrast to the aforementioned scores, the activity score could have less influence on impression formation.

The activity score might give insights into the actual networking behavior of the proprietor. It can give users an idea of how often a person logs in and/or makes updates to his/her profile, reacts to others' activities, or engages in communication. To our knowledge, there are no studies focusing on the impact of activity scores in SNS such as Instagram, Twitter, or BNS that we can refer to. However, Forrett and Dougherty (2004) found that "[e]ngaging in professional activities [offline] was related to… perceived career success" (p. 431). We suggest that being active on a BNS could indicate communicative ability as well as someone's effort to engage in the network and make a good impression. We assume that a high activity score could positively influence the wish to employ the proprietor. Moreover, Judge, Bono, Ilies, and Gerhardt (2002) have found that activity is positively associated with leader emergence and effective leadership. For this reason, the activity score could also affect ratings of destructive leadership behavior.

H5: A high activity score leads to higher ratings on employability than a low activity score does.

H6: A high activity score leads to lower ratings on destructive leadership behavior than a low activity score does.

1.4 The Impact of Aggregated Data on Equality

Little is known about the power of aggregated data in HRM on impression formation. Because aggregated data are based on predetermined algorithms it seems reasonable to ask "whether the available data in transactional HRIS [Human Resource Information Systems] are actually suitable for decision support purposes because they primarily reproduce HR decisions of the past" (Strohmeier & Piazza, 2013, p.2415). These decisions can comprise, for example, favoring elite university graduates or candidates with certain grades. Strohmeier and Piazza (2013) argue that this is neither new nor useful. Nonetheless, they see the potential to use aggregated data to refrain from previous hiring policies and allow for more diversity among applicants.

Discrimination, which represents the behavioral component of stereotypes (cognitive) and prejudices (affective), in the HR context means that applicants are not treated equally because they belong to certain groups, for instance, those who did not receive their degrees at elite universities or more simply women or transgender people. Owing to its immediate availability, sex is a very strong cue in person perception, which is automatically processed. While the term sex refers to the distinction between male and female based on a person's biological or physiognomic characteristics, the term *gender* refers to a person's sociological characteristics and to the question of whether the individual feels themselves be more feminine, masculine or androgynous (e.g., Bem, 1977). We will use both terms: *sex* when we refer to mere physiognomic characteristics (see Brown & Perrett, 1993) and *gender* when we refer to research in terms of stereotypes. The sex cue can decisively guide impression formation based on gender stereotypes (e.g., Fiske & Stevens, 1993), which comprise general beliefs that men are assumed to be competent and women to be caring (Cuddy, Fiske, & Glick, 2008; Fiske & Depret, 1996; Prentice & Carranza, 2002; Rudman & Glick, 2012) and in the context of leadership that men act in a more agentic way, while women are more communally oriented (Duehr & Bono, 2006; Eagly, & Johannesen-Schmidt, 2001; Koenig, Eagly, Mitchell, & Ristikari, 2011; Schein, 1973, 1975).

Indeed, although women make up about half of the workforce, they are still under-represented in leading positions,

which is often traced back to gender stereotypes (Cook & Glass, 2014; Eagly, 2007; Eagly & Carli, 2007; Eagly & Sczesny, 2009; Ellemers, Rink, Derks, & Ryan, 2012; Ridgeway, 2011). In the current context, this would, for instance, mean that female BNS proprietors receive lower ratings on employability with regard to a leading position. Research on warranting theory has provided the first evidence that single cues can be effective as heuristics. Schouten et al. (2015) demonstrated that simple profile elements, such as photos, affect impressions. In line with this, we assume that the sex cue in the poprietor's profile can function as another simple cue. Although Schouten et al. (2015) report that the photo never outperformed the impact of the resume, it was, nevertheless, strong enough to increase or decrease ratings. Further evidence for our assumption is given by Van der Heide and Lim (2016), who revealed that heuristics are more important for impression formation than system-generated information, especially for unfamiliar users of a website.

Following Strohmeier and Piazza's (2013) suggestion that aggregated data might prevent discrimination, we wanted to examine whether the different aggregated scores are perceived differently depending on the gender of the profile proprietor. If there is no difference, this will underline the power of aggregated data for impression formation and equality goals. Therefore, we state three research questions concerning the three aggregated scores:

RQ1: How do the commonality score and sex cues interact in terms of the attribution of (a) employability and (b) destructive leadership behavior?

RQ2: How do the contact score and sex cues interact in terms of the attribution of (a) employability and (b) destructive leadership behavior?

RQ3: How do the activity score and sex cues interact in terms of the attribution of (a) employability and (b) destructive leadership behavior?

2 Method

2.1 Stimuli

While most researchers have used interviews to investigate employability and especially destructive leadership behavior, we conducted an online experiment to determine the actual influence of aggregated data. To test our hypotheses, we designed profiles based on original profile layouts from the BNS XING, which is, besides LinkedIn, the most popular BNS in Germany. The 2 (low vs. high number of commonalities) × 2 (low vs. high number of contacts) × 2 (low vs. high activity level) × 2 (male vs. female profile proprietor) between-subjects design resulted in 16 different profiles of Junior Product Manager. The job history depicted the person as a junior product manager with marketing tasks in the telecommunications branch, who had been a trainee before and had worked as a student assistant in this area as well. Attractiveness is a decisive cue in person perception, also influencing job opportunities (Dion, Berscheid, & Walster, 1972; Dipboye & Dhahani, 2017; Heilman & Saruwatari, 1979), and attractiveness represents an important cue for recruiters (Zide et al., 2014), too. Moreover, style characteristics, such as wearing glasses, might also affect decisions regarding employability (Carr et al., 2017). In addition, Schouten et al. (2015) and Carr et al. (2017) have demonstrated that the profile picture influences the attributions that observers make of a profile proprietor, such as competence, and whether this person gets a job offer. To prevent any judgments about the profile picture while ensuring the high credibility of the profile, the profile owner's picture was blurred. The credibility of the basic profile with job history information and blurred picture was ensured by asking several students and practitioners for their general evaluation of the profile in a qualitative interview procedure. In line with the variables of interest, namely, the indices commonality, contacts, and activity, 22 participants in a pretest evaluated eight different manifestations for each of the indices with respect to the level of the value (e.g., "Please indicate how much you consider the contacts index to be low or high"; 1 = *low*, 7 = *high*) and its credibility ("How credible is the information for you?", 1 = *not credible*, 7 = *credible*). According to Tong et al. (2008), the final scores had to differ significantly with respect to low/high ratings but should not differ significantly regarding their attributed credibility.

The analysis of two repeated measurements for each index revealed several suitable combinations. Instead of choosing extreme values (e.g., 2 and 370 contacts, 10% and 90% activity), we decided to choose moderate values to obtain credible combinations of the indices (e.g., combining 2 contacts with 90% activity seems unlikely). Finally, we selected a number of 2 as a low (M = 1.79; SD = 0.85) and 39 as a high (M = 5.13; SD = 1.46) number of commonalities, 72 contacts as a low score (M = 3.65; SD = 1.43) and 246 (M = 5.52; SD = 1.59) as a moderate score, 20% as a low activity index (M = 2.55; SD = 0.80) and 80% (M = 5.41; SD = 0.96) as a high activity index. For an example of how the indices were displayed, see Figure 1.

Figure 1: Example for stimulus material

Participants were randomly assigned to the experimental conditions. Each participant viewed and evaluated only one of the 16 vignettes and answered questions regarding the dependent variables.

2.2 Measures

If prior to the data analysis a preliminary study was carried out, briefly describe the results at the beginning of the results section. This can for example be a summary of varying results to an overall index or the conversion of negative polarized items in the questionnaire.

2.2.1 Probability of Employment

We captured the probability of employment in a leading position with one item: "How likely is it that you would hire the person on the profile as a senior manager?" (1= *very unlikely*; 5 = *very likely*). In addition, we asked: "How confident are you with your decision?" (1= *very confident*; 5 = *very unconfident*).

2.2.2 Destructive Leader Behavior

We measured destructive leader behavior with the inventory by Thoroughgood, Tate, Sawyer, and Jacobs (2012). The inventory consists of three subscales: subordinate-directed behavior (14 items, e.g., "Avoids addressing important issues," "Fails to give subordinates credit for jobs requiring a lot of effort"), organization-directed behavior (11 items, e.g., "Steals company funds," "Accepts financial kickbacks"), and sexual harassment behavior (three items, e.g., "Hints that sexual favors will result in preferential treatment"). Answers were given on a 5-point scale (1 = *never*; 5 = *very often*). Each subscale showed good internal consistency values: subordinate-directed behavior: α = .90, *N* = 649; organization-directed behavior: α = .92, *N* = 648; sexual harassment behavior: α = .74, *N* = 649).

2.2.3 Demographic Variables

Some demographic variables were assessed, asking for the person's sex (male, female, refuse to answer), age, and familiarity with the social media applications XING, LinkedIn, and Facebook on 5-point Likert scales (1 = *I don't use it*, 5 = *I use it very often*). Participants were also asked for their experience in personnel selection (5-point scale, 1 = *no experience at all*, 5 = *very experienced*) and the years of work experience. Moreover, they were asked if they were or had been employed at any of the companies mentioned in the profile and asked to indicate their current status and their highest educational achievement.

2.2.4 Manipulation Check

As a manipulation check, participants were asked to select from lists the depicted person's gender, branch (e.g., Finance, Medicine, Marketing), and current position (e.g., Trainee, Junior Product Manager, Senior Manager). Only those who passed the manipulation check were considered for further analyses.

2.3 Participants

The original sample consisted of 665 participants; the final sample comprised 650 persons. Ten participants were removed because they did not pass the manipulation check, five others were removed because they had been or were currently employed at one of the organizations mentioned in the stimulus. The average age was 26 years (*M* = 26.16, *SD* = 14.42); 64.6% of the respondents were female, 34.4% male, 0.8% refused to reply. Three persons indicated to have completed junior high school, 15 completed high school, 381 achieved a general qualification for university entrance/A-level, 234 held a university degree, 16 held some other qualification (e.g., PhD), and one person did not have any formal qualification. Moreover, two were pupils, 457 were students, 125 were employees, 30 were self-employed, six were civil servants, 13 were unemployed/jobless, and 17 declared to be something else (e.g., freelancer). On average, participants were very familiar with Facebook (*M* = 4.04; *SD* = 1.34), they were less familiar with XING (*M* = 1.78; SD = 1.21) and LinkedIn (*M* = 1.39; *SD* = 0.91). They were short in experience with personnel selection (*M* = 2.11; *SD* = 1.20).

2.4 Procedure

The study was conducted online using the free online platform www.soscisurvey.de. The link leading to the study was distributed via various social media channels, for example, Facebook, XING and Twitter, as well as on message boards. The starting page informed participants about the goal of the study, that is, exploring people's professional self-presentation on the Internet, as well as about the estimated duration for completing the questionnaire, that is, 15 min. It was clarified that the collected data would be handled anonymously and only used for scientific purposes. The introductory text also mentioned the opportunity to take part in a lottery after having completed the study.

After being confronted with the stimulus of their condition, participants were asked to provide their impression via the Destructive Leadership Behavior items as well as hiring probability followed by the different manipulation checks and various sociodemographic and social media usage questions. At the end, participants were thanked for their participation and fully debriefed. They were given the opportunity to leave comments on the study. On a separate page they had the chance to enter their email address to take part in the lottery.

3 Results

To examine our hypotheses and research questions concerning employability (H1, H3, H5, RQ1a, RQ2b, RQ3a), we conducted an ANOVA with all indices and sex as independent variables and employability rating as the dependent variable.

The ANOVA concerning employability revealed that H1, H3, and H5 could not be supported as none of the indices was statistically significant, commonality, $F(1, 694.77) =$

0.00, p = .949, η^2_p = .000; contacts F(1, 694.77) = 0.08, p = .370, η^2_p = .001); activity F(1, 694.77) = 1.75, p = .187, η^2_p = .003. Concerning the research questions on the interaction effects of the sex cue and the indices, the analysis did not show significant interaction effects for the commonality index (RQ1a) and the contact index (RQ2a).

However, the interaction effect of the activity index and sex was significant (RQ3a), F(1, 694.77) = 4.42, p = .036, η^2_p = .007. Descriptive data showed that there is no sex preference for employment when the activity index is high (M_{men} = 2.91; SE = 0.09, M_{women} = 2.98; SE = 0.08); however, when the activity index is low there is a preference for women (M_{men} = 2.84; SE = 0.08, M_{women} = 3.26; SE = 0.08). To examine whether this result was caused by the structure of the sample (over-representation of women), we ran the same analysis including participants' sex as an additional independent variable. However, the interaction effect of participants' sex, profile proprietors' sex, and the activity index was not significant, which excludes participants' sex as a cause.

To test our hypotheses and research questions regarding destructive leadership behavior (H2, H4, H6, RQ1b, RQ2b, RQ3b), we conducted a MANOVA with all indices and sex as independent variables and all three dimensions of destructive leadership behaviors as dependent variables. The analysis yielded nonsignificant results (see Table 1) for the contact index (H2) as well as for the activity index (H6). In contrast to this, the commonality index was statistically significant with regard to organization-directed behavior. A lot of commonalities led to a lower rating on destructive organization-directed behavior (M = 1.75; SE = 0.04), while little commonality led to a higher evaluation of destructive organization-directed behavior (M = 1.88; SE = 0.04).

Regarding the interaction effects of the indices and the sex of the profile proprietor, the analyses did not reveal any statistical significance.

Table 1. Simple Effects of Indices and Interaction Effects of Indices*Gender on Destructive Leadership Behavior

Index	Destructive leadership behavior	F (1, 630)	p	η^2
Commonality				
	subordinate-directed behavior	0.04	.833	.000
	organization-directed behavior	**5.72**	**.017**	**.009**
	sexual harassment	3.45	.064	.005
Contacts				
	subordinate-directed behavior	0.51	.476	.001
	organization-directed behavior	0.18	.675	.000
	sexual harassment	0.00	.994	.000
Activity				
	subordinate-directed behavior	0.00	.990	.000
	organization-directed behavior	1.61	.205	.003
	sexual harassment	0.38	.541	.001
Index x Gender		F (1, 630)	p	η^2
Commonality x Gender				
	subordinate-directed behavior	1.72	.190	.003
	organization-directed behavior	0.17	.684	.000
	sexual harassment	0.16	.692	.000
Contacts x Gender				
	subordinate-directed behavior	0.41	.520	.001
	organization-directed behavior	2.18	.140	.003
	sexual harassment	1.41	.235	.002
Activity x Gender				
	subordinate-directed behavior	0.91	.341	.001
	organization-directed behavior	0.01	.909	.000
	sexual harassment	1.10	.295	.002

4 Discussion

The aim of the current study was to determine the impact of aggregated data on impression formation and, thereby, extend our knowledge about and scope of warranting theory. In addition, we wanted to examine whether aggregated data can be beneficial with regard to equality goals in the HRM context. For this purpose, we conducted an online experiment in which we systematically varied the presence of aggregated data in the form of different index values (e.g., moderate number of contacts vs. low number of contacts) as well as the sex of the profile owner (women vs. men) and captured the impressions of employability and destructive leadership behavior.

Our analysis revealed that the indices did not directly affect the perception of employability. Concerning destructive leadership behavior, we found that the commonality score affected the attribution of organization-directed behavior. The higher the number of shared commonalities, the less destructive the behavior toward the organization. This is in line with the law of attraction (Byrne & Rhamey, 1965) and underlines its power in person perception. Moreover, this finding is also congruent with findings that decision-makers prefer applicants who share some similarities with them (e.g., Gallois et al., 1992; García et al., 2008). This result indicates that participants had a positive self-concept regarding the working place, which excludes detrimental behavior toward their organization. One could scrutinize why the other two subscales (destructive against subordinates and sexual harassment) did not yield statistically significant results. We assume that participants may lack the experience of how to behave toward subordinates, because they had not yet reached a leader position. Thus, it could have been difficult for them to imagine whether they would, for instance, address important issues with their subordinates or not. In addition, the activity score and the contact score did not significantly influence the impression formation toward destructive leader behavior.

Referring to Strohmeier and Piazza (2013), we posed three research questions addressing equality issues concerning person perception. Arguing that aggregated data could diminish differences between the stereotypical perception of female and male job candidates (e.g., Cook & Glass, 2014; Eagly et al., 2001; Koenig et al., 2011), we found essential support for the beneficial effect of aggregated data: None of the scores interacted with sex with respect to destructive leadership behavior, and neither the commonality scores nor the contact scores influenced the impression of employability depending on the profile proprietor's sex. One exception is the activity score and employability. Our analysis showed that in the case of high activity there is no sex difference in employability ratings, while low activity leads to a preference for female candidates. After additional analyses, we could exclude the composition of our sample (overrepresentation of women) as a cause of this result. Women, in contrast to men, seem to be rewarded when they show low activity on the network, independent of the evaluator's sex.

What are the consequences for warranting theory based on our results? In contrast to former results (Tong et al., 2008; Utz, 2010; Walter et al., 2008), we could only find weak support for the direct effect of aggregated data on impression formation.

We see two possible reasons: First, the warranting value of aggregated data for impression formation is generally weaker than Walther and Parks (2002) as well as DeAndrea (2014) suggest, and second, the examined dimensions (employability and destructive leadership behavior) are out of the scope of warranting theory. Regarding the first explanation, previous studies reported contrary results. However, in studies like, for instance, those by Utz (2010), only one aggregated indicator (number of contacts) was researched, and comparable data for the impact of other aggregated indicators are lacking in the literature (DeAndrea, 2014). We extend the literature in this area by focusing on three aggregated indicators increasing the chance threefold that one indicator affects impression formation. Moreover, the considered aggregated scores differed in their likelihood of controllability by the profile proprietor. We found some evidence that the commonality score, which is at least controllable for a profile proprietor, has some effect on impression formation, while scores with more controllability (activity, contacts) did not affect the impression of employability and destructive leadership behavior. This results in the second explanation, that the captured dimensions of impression formation are out of the scope of warranting theory. It is possible that only very basic inferences are influenced by aggregated data, such as credibility or social attractiveness (e.g., Antheunis & Schouten, 2011; Tong et al., 2008; Utz, 2010). Employability and destructive leadership behavior can be overly powerful impressions, which may be easier predicted by self-generated data in the form of self-reports (García et al., 2008; Riviera, 2012). However, Carr et al. (2017) have demonstrated that employability ratings are affected by self- and other-generated data. For this reason, it is possible that only system-generated aggregated data are not powerful enough to influence this dimension. Besides the different types of information used in the current study and in the study by Carr et al. (2017), the latter focused on short contracts (Fiverr platform), while our settings suggested a long-term contract with employee responsibility. It can be that these characteristics influence attributions. We assume that more research is needed to determine the power of aggregated data in the realm of warranting theory.

While our findings do not support warranting theory, they are conducive to the application of data mining in HRM. It seems that aggregated data do not force impression formation in a strict way, despite person perception processes running automatically most of the time (Bargh & Chartrand, 1999; Chartrand & Bargh, 1999). Moreover, regarding equality issues (Strohmeier & Piazza, 2013), aggregated data do not reinforce stereotypical gender differences (e.g., Eagly & Carli, 2007), which can be beneficial for women applying for a leading position in future. Under these circumstances data mining can be applied, at least on BNS, to support decision-makers by reducing a huge number of cues into single indicators. This is also in line with claims by Li et al. (2008). However, we want to stress the importance of data quality, for instance, who is

in the contact list, which can get lost when reducing data (see Eimler, Sauer, & Krämer, 2016). Following the assumptions of Strohmeier and Piazza (2013), we assume that algorithms for data mining should be carefully considered, not because of their impact on person perception, but for their opportunity to encourage diversity.

Although our results are in favor of data mining and do not indicate detrimental attributions, further studies are needed to provide more empirical evidence, and therefore other less powerful dimensions of impression formations than those we focused on could be investigated, such as communication skills. This can help to determine the impressions that are affected by warranting theory. In addition, conducting more research on aggregated data allows us to find out which characteristics aggregated data need to affect impression formation.

Moreover, one could argue that our sample was not appropriate to test our hypotheses owing to the high number of students and women. However, our hypotheses refer to basic processes in person perception, which every person is subject to (see Bargh & Chartrand, 1999, Chartrand & Bargh, 1999; Cuddy et al., 2008). In addition, several studies in the HRM context have shown that professional decision-makers focus on the same information in recruitment as inexperienced persons do (e.g., Jansen et al., in press; Posner, 1981; Ruetzler et al., 2011, Ruetzler et al., 2012; Wood et al., 2007; Zhao, 2006). Furthermore, the high number of participating women in experimental and survey studies is very common (e.g., Aiman-Smith, Bauer, & Cable, 2001; Allen, Biggane, Pitts, Otondo, & Van Scotter, 2013; Saks & Uggerslev, 2010; Utz, 2010; Walther et al., 2009). To figure out whether the high number of women has influenced our results, we conducted additional analyses, but the results were not statistically significant. However, to give more evidence for our findings, our study could be replicated with a more balanced sample and a more professional sample.

In conclusion, we found that aggregated data did not affect person perception with respect to employability and destructive leadership behavior in a detrimental way; additionally, stereotypical processes were not reinforced. As a consequence, it seems that data mining is a useful tool for reducing a high amount of information into single indicators and thus to facilitate decision-making. Nevertheless, system engineers bear great responsibility because they have to define algorithms that reduce data, support decision-making, and allow for diversity.

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