Same but Different – How Users Benefit in Online Peer Groups Depending on their User Role

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SAME BUT DIFFERENT – HOW USERS BENEFIT IN ONLINE PEER GROUPS DEPENDING ON THEIR USER ROLE

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Abstract

The enormous potential of online peer groups in addressing social problems has attracted researchers’ attention to investigate how users support each other and benefit from participation. The extent, how users benefit in online peer groups depending on their role of contributing social support is still unexplored. To close this gap, we analyse a unique online peer group dataset in the context of unemployment from a field experiment at the German Federal Employment Agency. We build on content analysis and cluster analysis to detect user roles based on users’ contribution in the form of exchanging social support. We quantitatively compare how different users benefit from participation. Results show that users generally benefit by means of peer group effects regardless of their role. However, low-contributors get disproportionately activated and thereby benefit in dimensions where they initially lag behind other users. High-contributors disproportionally benefit in terms of acquiring pertinent skills.

Keywords: Online Peer Group, User Role, Social Support, Societal Value of IS.

1 Introduction

Already primates grouped into communities for cooperative hunting and thereby created the basis for humans to become a zoon politikon (Gintis et al., 2018). Today, online communities represent a cornerstone of human interaction (Cullen and Morse, 2011; Seering et al., 2019), enabled through the rise of Information and Communication Technologies (ICT). In crisis, such as the pandemic of COVID-19, ICT are becoming even more relevant for maintaining social relationships (Gabbiadini et al., 2020). In online communities, groups of people with common interests, beliefs and values interact through online mediation (Cullen and Morse, 2011). The distinction between consumers and producers collapses; instead, users at the same time contribute and benefit from the content shared digitally (Malinen, 2015). At the same time, there is extremely uneven participation: In most online communities, 90% of users never contribute, 9% sometimes do, and 1% produce almost all the content (Nielsen, 2006). Thus, research tries to understand user roles, i.e. users’ manner and patterns of behaviour in online communities (Akar and Mardikyan, 2018). Most prominently, research investigates lurkers, who only consume, and posters, who actively produce content (Bozkurt et al., 2020).

User behaviour plays an extraordinary role in online peer groups (Zhao et al., 2014). Among online communities, online peer groups are characterised by users that typically share a common need, handicap or desired social/personal change and support one another to overcome their challenging situation or better deal with it (Katz and Bender, 1976; Felgenhauer et al., 2019b). Online peer groups have been proven successful in assisting people in various contexts, for instance, health-related contexts like cancer (Zhang et al., 2017), depression (Prevatt et al., 2018), and chronic disease (Wang et al., 2017), but also addiction (Graham et al., 2017) and unemployment (Felgenhauer et al., 2019a). Users benefit from peer group effects which may manifest as an increase of general well-being (Prevatt et
al., 2018), positive behaviour change (Klier et al., 2019), increase of knowledge (Niela-Vilén et al., 2014), and increase of self-efficacy (Wang et al., 2017). The foundation of why online peer groups are effective is the exchange of social support, i.e. assistance shared to and received from other users (Coulson et al., 2007). While sharing social support seems to be (only) a contribution to others at first glance, research suggests that users might as well benefit from it by means of emotional relief and personal empowerment (Barak et al., 2008). But which users benefit more in online peer groups – those who actively support others thereby contributing to the group or those who do not?

To date, no study exists that investigates how users in online communities benefit from participation depending on their role of contributing social support. To close this gap, in our paper we address the following research question: How do different users in online peer groups, depending on their role of contributing social support, benefit from participation? To get first insights, we analyse a unique dataset containing data from online peer groups in the context of unemployment, obtained from a randomized field experiment conducted at the German Federal Employment Agency. We determine user roles in online peer groups based on users’ contribution in the form of exchanging social support and compare to what extent different users benefit by means of desired peer group effects.

We identify low-contributors and high-contributors as user roles in our study and find that both groups of users benefit from participation. However, users significantly differ in how they benefit: Low-contributors disproportionately increase their job search intensity and thereby catch up in a dimension where they initially lag behind other users. Contrarily, high-contributors disproportionately acquire pertinent skills. The contribution of our paper is twofold. We are the first to shed light on how different users in online communities, depending on their role of contributing social support, benefit from participation. Further, we expand literature on online peer groups by quantitatively comparing the extent of how low-contributors and high-contributors benefit by means of peer group effects.

The remainder of this paper is as follows: Section 2 provides an overview of the related work. In Section 3, we describe our case setting, the dataset and the research method used. Then, in Section 4, we present our results based on a unique dataset from a field experiment in cooperation with the German Federal Employment Agency. We critically discuss implications and limitations of our research and provide directions for further research in Section 5. Finally, we conclude with a summary.

2 Theoretical Background and Related Work

2.1 Online peer groups and peer group effects

Peer groups are networks of people “who have come together for mutual assistance in satisfying a common need, overcoming a handicap or bringing about desired social and/or personal change” (Katz and Bender, 1976, p. 278). Peer groups differentiate from other forms of communities by participants that share a challenging situation and aim to improve this situation or the way they deal with it (Katz and Bender, 1976; Felgenhauer et al., 2019b). A prominent example is Alcoholics Anonymous, which already connected people suffering from alcoholism in the middle of the 20th century (Gross, 2010). In recent years, peer groups that interact through computers or mobile communication networks, i.e. online peer groups, have gained increasing attention (Huber et al., 2018). Literature proposes online interaction to facilitate mutual support among peers (Klier et al., 2019). Compared to traditional face-to-face peer groups, online peer groups provide time- and location-independent access to support (van Uden-Kraan et al., 2008b), the possibility to spend more time for an utterance instead of answering to a statement instantly (Coulson, 2013), and a larger degree of anonymity, which encourages people to talk about sensitive issues and share opinions (van Uden-Kraan et al., 2008b; Coulson, 2013).

Research in diverse disciplines including psychology, economics, and information systems has investigated online peer groups’ potential to address social problems (Barak et al., 2008) and create social value (Goh et al., 2016). Interaction in online peer groups affects participants by means of peer group effects, i.e. the “change in the belief, attitude or behavior of a person […] which results from the action or presence [of a peer or group of peers]” (Erchul and Raven, 1997, p. 138). The presence of dif-
different forms of peer group effects has been proven in various contexts, among others physical and mental health (Holbrey and Coulson, 2013; van Ingen et al., 2016), caregiving (O’Connor et al., 2014), alcohol and smoking addiction (Cunningham et al., 2008; Graham et al., 2017), parenting (Niela-Vilén et al., 2014), unemployment (Felgenhauer et al., 2019a), and social isolation (Goswami et al., 2010). For instance, the peer group effect increase of general well-being has been observed in online peer groups for women with postpartum depression (Prevatt et al., 2018) and people having experienced negative life events (van Ingen et al., 2016). Furthermore, peer group effects may manifest as positive behaviour change in that people increase their level of physical activity (Cavallo et al., 2014), smokers overcome smoking addiction (Graham et al., 2017), or unemployed youths increase their career search intensity (Klier et al., 2019). Another peer group effect is the increase of knowledge, which has been for instance found in online peer groups for parents, who learned to better understand the role of parenting through interacting with peers (Niela-Vilén et al., 2014). Finally, online peer groups have been found to induce an increase of self-efficacy, i.e. the “beliefs in one’s capabilities to organize and execute the courses of action required to produce given attainments” (Bandura, 1997, p. 3). For instance, patients with stigmatized chronic diseases in online peer groups reported to improve self-care behaviour (Wang et al., 2017) and teachers forming an online peer group increased self-efficacy for creative teaching (Chung and Chen, 2018).

2.2 Social support in online peer groups

The theoretical foundation of interaction in peer groups is social support (Coulson et al., 2007). Social support is defined as assistance provided and received from individuals of a social network (Vaux, 1988) and describes the individuals’ behaviour (cf. Section 3). To illustrate, peers from Alcoholics Anonymous might share experiences on how to cope with alcoholism and give each other hope. While the concept of social support has at first been described by research on offline peer groups, it has later been confirmed to be valid for online peer groups as well (e.g. Coulson et al., 2007). Literature distinguishes between five types of social support (Cutrona and Suhr, 1992), which are shown in Table 1.

<table>
<thead>
<tr>
<th>Type of social support</th>
<th>Description</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Informational support</td>
<td>Information, explanations, facts, experiences, personal advice, referrals to experts</td>
<td>Finn (1999); Coulson et al. (2007)</td>
</tr>
<tr>
<td>Emotional support</td>
<td>Empathy, solidarity, disclosure of similar challenging situations in one’s own life, feelings, such as regret, concerns, worries, desires, understanding, and affection</td>
<td>Weinberg et al. (1996); Braithwaite et al. (1999); Coursaris and Liu (2009)</td>
</tr>
<tr>
<td>Esteem support</td>
<td>Positive communication, such as compliments, recognition, appreciation, acknowledgment, respect, and jokes, validation of others’ self-concept, competence, and importance</td>
<td>Braithwaite et al. (1999); Coursaris and Liu (2009); Felgenhauer et al. (2019b)</td>
</tr>
<tr>
<td>Network support</td>
<td>Companionship, feelings of not being alone, encouragement of building trusting relationships, identification of similarities with others and their situations</td>
<td>Coulson et al. (2007); Gaysynsky et al. (2015); Felgenhauer et al. (2019b)</td>
</tr>
<tr>
<td>Tangible assistance</td>
<td>Material support or physical service, such as loaning goods or expressing the intention to do so</td>
<td>Coursaris and Liu (2009); Gaysynsky et al. (2015)</td>
</tr>
</tbody>
</table>

Table 1. Overview on types of social support.

Prior research found social support in online peer groups to be responsible for peer group effects. First, studies on online peer groups in health-related contexts indicate that social support evokes an increase of general well-being in that patients improve in terms of life satisfaction (Oh et al., 2014), stress, depression, coping (Beaudoin and Tao, 2007), and perceived empathy (Nambisan, 2011). These effects are directly linked to positive health outcomes (Beaudoin and Tao, 2007) and patients’ recovery (Nambisan, 2011). Second, studies propose that social support fosters positive behaviour change. For instance, breast cancer patients who received higher levels of social support from peers in online peer...
groups exhibited fewer breast cancer-related concerns (Kim et al., 2012). Last but not least, receiving social support from peers in online peer groups has been shown to assist participants in managing serious illnesses (Yoo et al., 2014) which represents an increase of self-efficacy in the context of health (Newton and Ashley, 2013).

To sum up, as social support both represents the theoretical foundation of interaction in online peer groups and seems to be responsible for observed peer group effects, users’ exchange of social support might well represent their contribution to the group.

2.3 User roles in online communities

The contribution of users in online peer groups is associated with their user role, i.e. their manner and patterns of behaviour within the group (Wang et al., 2016; Akar and Mardikyan, 2018). In fact, user roles have attracted wide interest among researchers investigating online communities (Angeletou et al., 2011; Wang et al., 2016; Akar and Mardikyan, 2018), which include online peer groups but are more generally defined (cf. Section 1). Literature considers the understanding of user roles as the foundation for observing and maintaining the “good health” (Angeletou et al., 2011, p. 36) and continuity of an online community (Füller et al., 2014; Wang et al., 2016).

The most prominent user roles identified in literature are posters and lurkers (Malinen, 2015). In contrast to posters, who actively interact with others in the community, lurkers consume content but (predominantly) do not participate in interaction (Setoyama et al., 2011; Petrovčić and Petrič, 2014; Alarifi et al., 2015; Phang et al., 2015; Fischer et al., 2016; Bozkurt et al., 2020). However, studies claim that a mere investigation of activity does not adequately describe user roles (Malinen, 2015). To illustrate, users can be very active in an asocial manner and thus a large volume of contribution is not necessarily an indication of interactivity (Shoham et al., 2013). Thus, researchers expanded this basic concept to capture users’ contribution to the community (Malinen, 2015). In the context of enterprise social networks, Cetto et al. (2018) distinguished content seeking and content providing within users’ interactions and on that basis derived three user roles: givers, who outstandingly provide content, takers, who mainly seek content, and matchers, who provide and seek content to a relatively balanced extent. Zhao et al. (2014) combined measures quantifying users’ interactions and sentiment analysis and determined influential users in online health communities, i.e. those who frequently contribute content that influences sentiment. Vydiswaran and Reddy (2019) additionally included social network metrics, such as PageRank and identified peer experts, i.e. users who assist others in improving their health, although lacking professional training. In the context of an innovation-contest community, Füller et al. (2014) combined cluster analysis and social network analysis to distinguish masters, which are superior to other user roles with respect to activity and contribution quality. User roles contributing most to the community have been found rare in online communities (Nielsen, 2006). For instance, 1% or less were identified peer experts in an online health community (Vydiswaran and Reddy, 2019) or masters in an innovation-contest community (Füller et al., 2014).

Aiming to align strategies for specific types of users, researchers analyse their behaviour (Akar and Mardikyan, 2018). First, studies investigate why specific users contribute more than others to online communities (Akar and Mardikyan, 2018; Badreddine and Blount, 2019; Bozkurt et al., 2020). For instance, external factors like time restrictions, individual factors like lack of interest (Bozkurt et al., 2020), extroversion, and openness-to-feelings as well as environmental factors, such as delayed responses to shared content (Badreddine and Blount, 2019) have been found to foster lurking. In contrast, image, i.e. the extent to which users believe that posting enhances their social self-concept, and intrinsic interest, i.e. the extent to which users are involved in the activity for their own pleasure, have been found to enhance contributing (Akar and Mardikyan, 2018). Second, literature examines how different types of users contribute to overall success of online communities (Xing et al., 2018; Davcheva et al., 2019). Davcheva et al. (2019) distinguished original posters from commenters and compared the sentiment of their messages, i.e. a success indicator depicting communities’ vitality (Bedué et al., 2020). Results suggest that commenters’ messages on average provide a higher sentiment score than original posters’ messages (Davcheva et al., 2019). Xing et al. (2018) explored how
informational support sent by different types of users (i.e. core users and periphery users) are related with other users’ retention in the community. They found that only support provided by core users is positively associated with continued participation (Xing et al., 2018). Both studies identified user roles based on messages (Xing et al., 2018; Davcheva et al., 2019). Third, researchers investigate how different users benefit from participation in online communities (van Uden-Kraan et al., 2008a; Mo and Coulson, 2010; Setoyama et al., 2011; Merry and Simon, 2012). van Uden-Kraan et al. (2008a) were the first to examine the connection of users’ participation behaviour and associated benefits. More precisely, they asked users of health-related online peer groups how often they post messages and whether they perceive empowering processes and outcomes. They found that lurkers do not differ from posters regarding the perception of most empowering outcomes (van Uden-Kraan et al., 2008a). Setoyama et al. (2011) also utilized surveys to identify lurkers and posters and compared how these types of users perceive benefits, such as mental health and peer support. Posters reported to receive more peer support from online communities than lurkers which was negatively correlated with anxiety (Setoyama et al., 2011). Other studies using a similar methodology found that posters perceive more useful information in empowering processes (Mo and Coulson, 2010), satisfaction (Mo and Coulson, 2010; Merry and Simon, 2012), and sense of community (Merry and Simon, 2012) than lurkers.

Despite these fascinating first insights, research to date investigating how users benefit from participation in online communities depending on their user role, is criticised for two reasons. First, existing research merely considers users’ activity as a determinant for their user role. Activity approximates well users’ volume of contribution, however, it neglects the content’s relevance for the community and thus does not adequately depict users’ contribution (Shoham et al., 2013; Malinen, 2015). Second, existing studies in this body of literature predominantly capture users’ self-reported usage behaviour and perceived benefit from participation via surveys. While this represents a first important step, results may be biased by users’ subjective evaluation. In fact, online interaction allows to more objectively identify user roles via the interpretation of recorded written data (Alarifi et al., 2015; Xing et al., 2018; Davcheva et al., 2019; Bozkurt et al., 2020). We aim to address these shortcomings. In this study, we analyse how different users in online peer groups benefit from participation, depending on their user role of contributing to the group. We measure users’ contribution in the form of messages that contain social support and thereby take into consideration the content’s relevance for the group (Coulson et al., 2007). We analyse how users benefit from participation by extracting peer group effects in a randomized field experiment including a control group (Klier et al., 2019).

3 Methodology

We aim to quantitatively compare how users in online peer groups, depending on their role of contribution, benefit from participation. Our analysis is based on a unique dataset in the context of unemployment from a field experiment with 413 unemployed people at the German Federal Employment Agency. First, to capture users’ contribution to the group, we identify social support in messages (Coulson et al., 2007) using content analysis (Krippendorff, 2004). Second, to determine user roles, we conduct a cluster analysis (Hacker and Riemer, 2020) based on users’ behaviour in the form of seeking and providing social support. Third, to assess to what extent different users benefit from participation, we statistically compare measures associated with desired peer group effects (Erchul and Raven, 1997) in the context of unemployment. In the remainder of this section, we provide an overview of the case setting, dataset, and measurement. Then, we describe the analysis in detail.

3.1 Case setting

The field experiment was conducted in cooperation with the German Federal Employment Agency (Bundesagentur für Arbeit) in the context of unemployment, one of society’s most relevant problems (ILO, 2020). The German Federal Employment Agency is the largest provider of labour-related services for citizens, companies, and institutions, with roughly 95,000 employees, 156 employment agencies, and about 600 branch offices in Germany. Services incorporate employment placement, career counselling, and financial support in cases of unemployment or insolvency of employers.
Conventionally, the German Federal Employment Agency offers one-on-one counselling between an employment counsellor and an unemployed individual. A new approach supplements this service with online peer groups for older unemployed people (at the age of 50 or older), realized via a mobile messaging application. About 20 people sharing the challenge of being unemployed at the age of 50 or older form an online peer group, where they exchange messages with text, emojis, and files, such as images in open discussions. The messenger allows to quote previous messages, still, all messages are visible to all participants in the group. An employment counsellor moderates and supervises the online peer group. Within the online peer groups, all unemployed people and the moderators remain anonymous while having a unique identification code. The approach was introduced in a field experiment where online peer groups were installed each over three months between February 2019 and June 2020. Employment counsellors attended a full-day workshop to be introduced in their tasks. Prior research has already confirmed social support to play a central role in online peer groups in the context of unemployment (Felgenhauer et al., 2019a).

### 3.2 Dataset and measurement

During the experiment, we collected two datasets: online peer group data and survey data.

First, to capture users’ behaviour in the online peer groups, we gathered the online peer group data which comprises all messages including text, emojis, and files as well as metadata including identification number of the writer, time stamp, and information on quotations of other messages from the field experiment. 467 unemployed people and 25 employment counsellors from 15 employment agencies, represented by a colleague in case of absence, participated in 25 online peer groups. Each unemployed individual and employment counsellor was assigned to one online peer group according to his/her assignment to an employment agency, as shared content, such as information about job offers, can regionally differ. Messages in all 25 online peer groups sum up to 5,741 messages with 4,127 messages being sent by older unemployed people.

Second, to capture the individuals’ benefit from participating in an online peer group, we collected survey data on success indicators predicting reemployment. These comprise job search intensity, job search skills, attitude towards job search, and digital competencies (Wanberg et al., 2002; McQuaid, 2006; Liu et al., 2014) and are associated with desired peer group effects in the context of unemployment (Felgenhauer et al., 2019a).

To operationalize the success indicators job search intensity and job search skills, we adopted established constructs from research on the effects of employment interventions in Germany (Schmidt, 2007; Klier et al., 2019). We used standard questionnaires to measure constructs on attitude towards job search (Jerusalem and Schwarzer, 1992; Schmitz and Schwarzer, 1999). Finally, as digital incompetence negatively influences job search among older unemployed people, we added constructs depicting basic digital competencies based on established questionnaires (European Union, 2015; Klier et al., 2020). The comprehensibility of the survey items was validated with professional counsellors at the Federal Employment Agency. Constructs were measured using a Likert-type scale ranged from 1 (“strongly disagree”) to 6 (“strongly agree”). The average of a construct’s items was realized for Likert-type scales with multiple items; the sum of a construct’s items was realized for nominal scales with multiple items. Table 2 provides an overview of constructs and success indicators.

In the field experiment, voluntarily participating older unemployed people were randomly assigned to either participate in an online peer group or a control group that further only received conventional one-on-one counselling. We asked all participants to complete a pre- and a post-survey (before and after three months). We count 200 older unemployed people in the online peer groups and 213 in the control group for further analysis, as they completed the pre- and the post-survey. These subjects include 237 men and 176 women with an age-span between 50-66. 35% of subjects have an academic degree and 26% a completed apprenticeship. Out of the remaining 39% subjects, 3 subjects do not have any school-leaving qualification.
Table 2. Overview on constructs and success indicators predicting reemployment.

3.3 Analysis

Our analysis includes identification of social support, detection of user roles, and comparison of users.

Identification of social support. We consider shared social support as users’ contribution. Like previous studies in this context (e.g. Felgenhauer et al., 2019b), we applied content analysis (Krippendorff, 2004) utilizing the Social Support Behavior Code (Cutrona and Suhr, 1992) as a coding scheme to identify social support in messages. Three researchers conducted coding independently from each other and discussed coding disagreements to reach consent. Messages could be coded as containing one or more types of social support, i.e. informational support, emotional support, esteem support, network support, and tangible assistance. If a message contained social support, the raters decided if the message provides and/or seeks social support. Interrater reliability measured by Fleiss’ Kappa was 0.73 – “substantial agreement” (Landis and Koch, 1977, p. 165). For the 200 online peer group users included in the analysis, we found 2,120 messages providing social support and 481 messages seeking social support. Social support within these messages comprised 62.8% informational support, 31.6% esteem support, 3.1% emotional support, 2.1% network support, and 0.4% tangible assistance, proportions which are in line with prior findings in this context (Felgenhauer et al., 2019b).

Detection of user roles. Inspired by Hacker and Riemer (2020), we used cluster analysis, an unsupervised learning method, to explore user roles, as “the roles that users can occupy are not predefined or specified in any way” (Wang et al., 2016, p. 73). We aggregated the number of messages seeking social support and the number of messages providing social support per participant and applied k-means clustering in R on these variables. Differentiating between content seeking and providing has been proven suitable to capture users’ contribution in online communities (Cetto et al., 2018). To determine the optimal number of clusters, we utilized the elbow method (Thornridge, 1953). It resulted in three clusters with an average silhouette score of 0.644, suggesting a strong clustering structure.

Comparison of users. To assess how users benefit from participation, we statistically compared constructs associated with success indicators predicting reemployment (cf. Table 2). For comparison, we
chose the Mann-Whitney U-test as a non-parametric alternative to the t-test because our data was not normally distributed. First, we compared the pre values of the constructs indicating the initial level when users entered the online peer groups. Second, we compared the post values of the constructs indicating the final level when users left the online peer groups. Third, we compared the difference (post-pre) values of the constructs indicating the users’ development during the three months. The focus of this study is to compare the development of users depending on their user role. Beyond, we compared the development of users in the online peer groups with the development of the control group, i.e. benchmark development, to extract benefit as an effect of participation (Klier et al., 2019).

4 Results

This section is dedicated to our findings. We first describe the results of the cluster analysis and present the user roles in our case setting. Second, we analyse how users in the online peer groups benefit from participation depending on their user role.

4.1 Description of user roles

The cluster analysis based on users’ behaviour in the form of providing and seeking social support results in three clusters. While all users send on average 10.6 messages providing social support and 2.4 messages seeking social support, the majority of users exchange less social support: Users in Cluster 1 represent 75% of all users and send on average 3.6 messages providing social support and 0.6 messages seeking social support. In contrast, users in Cluster 2 and Cluster 3 exchange more social support than average. Users in Cluster 2 (18.5% of all users) send on average 22.3 messages providing social support and 5.4 messages seeking social support. Users in Cluster 3 (6.5%) send on average 58.5 messages providing social support and 14.5 messages seeking social support. Clusters are characterized by either a relatively low or high number of both messages providing and seeking support.

We further analyse the clusters with respect to their initial level of constructs representing success indicators for reemployment (cf. Table 2). Users in Cluster 2 and Cluster 3 do not significantly differ in their initial level of all constructs according to Mann-Whitney U-tests. As further, both clusters are rather small and users in the two clusters provide similar usage behaviour in sending more messages providing and seeking social support than average, we combine users in Cluster 2 and Cluster 3 and refer to those as high-contributors. Users in Cluster 1 are referred to as low-contributors. Usage behaviour and initial level of constructs associated with these user roles are summarized in Figure 1.

![Figure 1](image_url)  
**Figure 1.** Description of user roles by users’ behaviour and mean initial level of constructs.
High-contributors, which represent 25% of all users, send more messages providing social support (mean=31.7) and seeking social support (mean=7.8) than low-contributors. They initially dominate low-contributors in constructs representing success indicators for reemployment: According to Mann-Whitney U-tests, high-contributors provide a significantly higher initial level of the constructs number of distinct application activities, number of applications, number of invitations to job interviews (all p<0.05), and number of distinct digital media applications used for job search (p<0.01). Regarding all other constructs, low-contributors and high-contributors do not significantly differ in initial level.

4.2 Analysis of users’ benefit depending on their user role

To compare how low-contributors and high-contributors benefit from participation, we first compare all users’ development in constructs against benchmark development to assess whether users benefit at all (see Table 3 for results). Second, we statistically compare low-contributors’ and high-contributors’ development to extract which users benefit more from participation. To deepen these insights, we further compare their final level (see Table 4 for results).

Figure 2 illustrates the results for the construct interview application skills. The Figure shows the average development of all users, benchmark development, and the average development of low-contributors and high-contributors. As shown on the left, users on average develop better than the benchmark and thus users generally benefit from participation. As shown on the right, high-contributors develop better than low-contributors, which indicates higher benefit from participation.

![Illustration of the results for the construct interview application skills.](image)

Both low-contributors and high-contributors benefit from participation in the online peer groups. As shown in Table 3, users in the online peer groups develop better than the benchmark with respect to the constructs number of distinct application activities, number of applications, job search clarity (all p<0.1), written application skills, and interview application skills (all p<0.01). This reveals positive peer group effects regarding the success indicators job search intensity and job search skills. Simultaneously, pairwise comparisons of low-contributors’ / high-contributors’ development and benchmark development reveals that both low-contributors and high-contributors at least develop as good as the benchmark. In sum, while overall positive peer group effects are observed in certain dimensions, no negative effects are observed for users associated with either user role.
Förster /Investigating Users’ Role and Benefit

<table>
<thead>
<tr>
<th>Success indicator</th>
<th>Construct</th>
<th>Z-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job search intensity</td>
<td>Number of distinct application activities</td>
<td>1.71*</td>
</tr>
<tr>
<td></td>
<td>Number of applications</td>
<td>1.69*</td>
</tr>
<tr>
<td></td>
<td>Number of invitations to job interviews</td>
<td>1.20</td>
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<tr>
<td>Job search skills</td>
<td>Written application skills</td>
<td>2.66***</td>
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<td></td>
<td>Interview application skills</td>
<td>3.08***</td>
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<td></td>
<td>Job search clarity</td>
<td>1.93*</td>
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<td>Attitude towards job search</td>
<td>Proactive attitude</td>
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<td></td>
<td>Self-efficacy</td>
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<tr>
<td>Digital competencies</td>
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<td></td>
<td>Number of distinct digital media applications used for job search</td>
<td>-0.22</td>
</tr>
</tbody>
</table>

Table 3. Results of the Mann-Whitney U-test for comparison of users’ development against benchmark development (*p<0.1, **p<0.05, ***p<0.01, ****p<0.001).

Low-contributors benefit more from participation than high-contributors in terms of activation. As shown in Table 4, low-contributors develop significantly better than high-contributors with respect to the construct number of applications (p<0.1), which is associated with job search intensity. While for the number of applications, an overall increase was observed for users of the online peer groups compared to the benchmark, low-contributors get disproportionately activated. Initially, low-contributors make a significantly lower number of applications than high-contributors at the 5% significance level. Low-contributors catch up to some extent but do not reach the level of high-contributors. Indeed, their final level is still lower than the high-contributors’ final level, but only at the 10% significance level. Moreover, low-contributors seem to get especially activated in their digital job search. They (non-significantly) develop better than high-contributors with respect to the construct number of distinct digital media applications used for job search and thereby catch up to some extent. While their initial level is lower than the high-contributors’ initial level at the 1% significance level, their final level is only lower at the 5% significance level. At the same time, low-contributors catch up with respect to basic digital skills, where they develop significantly better compared to high-contributors (p<0.1). They do not pass the high-contributors’ final level.

<table>
<thead>
<tr>
<th>Success indicator</th>
<th>Construct</th>
<th>Z-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job search intensity</td>
<td>Number of distinct application activities</td>
<td>-2.14**</td>
</tr>
<tr>
<td></td>
<td>Number of applications</td>
<td>-2.16**</td>
</tr>
<tr>
<td></td>
<td>Number of invitations to job interviews</td>
<td>-2.33**</td>
</tr>
<tr>
<td>Job search skills</td>
<td>Written application skills</td>
<td>-0.39</td>
</tr>
<tr>
<td></td>
<td>Interview application skills</td>
<td>1.25</td>
</tr>
<tr>
<td></td>
<td>Job search clarity</td>
<td>-0.72</td>
</tr>
<tr>
<td>Attitude towards job search</td>
<td>Proactive attitude</td>
<td>-0.90</td>
</tr>
<tr>
<td></td>
<td>Self-efficacy</td>
<td>-0.63</td>
</tr>
<tr>
<td>Digital competencies</td>
<td>Basic digital skills</td>
<td>-1.25</td>
</tr>
<tr>
<td></td>
<td>Number of distinct digital media applications used for job search</td>
<td>-2.96***</td>
</tr>
</tbody>
</table>

Table 4. Results of the Mann-Whitney U-test for comparison of low-contributors’ against high-contributors’ initial level, final level, and development (*p<0.1, **p<0.05, ***p<0.01, ****p<0.001).
High-contributors benefit more from participation than low-contributors in terms of pertinent skill acquisition. High-contributors develop significantly better than low-contributors with respect to the construct interview application skills (p<0.05), which is associated with the success indicator job search skills. Overall, users in the online peer groups develop better than the benchmark with respect to this construct, however, high-contributors disproportionately improve their interview application skills. Regarding the other constructs associated with job search skills, i.e. written application skills and job search clarity, high-contributors and low-contributors do not significantly differ in development. While particularly improving job search skills, high-contributors also expand their lead in being invited to job interviews. While their initial number of invitations to job interviews is already higher than the low-contributors’ initial level at the 5% significance level, their final level is even higher at the 0.1% significance level.

5 Discussion

5.1 Implications for research and practice

With our work, we aimed to shed light on how users benefit from participation in online peer groups depending on their user role. In contrast to prior research, we investigated user roles based on users’ contribution in the form of messages that contain social support. Conducting a randomized field experiment allowed us to explicitly extract users’ benefit from participation. We analyzed a unique dataset comprising 413 unemployed people. In the following, we discuss our findings.

First, our results suggest that user roles in online peer groups for older unemployed people provide characteristics that are common for user roles in online communities in general. We find 75% of all users to be low-contributors and 25% to be high-contributors. Low-contributors represent the majority of users like in most online communities (Nielsen, 2006), however, they are comparably underrepresented in our study. This might be explained by the purpose of online peer groups, as participants aim to improve a challenging situation through mutual support (Felgenhauer et al., 2019b). Beyond, older unemployed people have been particularly found “willing to participate in digital services increasing their chance for reemployment” (Klier et al., 2020, p. 12). In our study, high-contributors use significantly more distinct digital media applications for job search than low-contributors. Thereby, high-contributors resemble the general digital user type Advanced Users (Brandtzæg, 2010) and social media type Heavy Users in the context of unemployment (Feuls et al., 2016). Contrarily, low-contributors reflect Sporadics and Lurkers who predominantly consume content (Brandtzæg, 2010), and Novices who are particularly hesitant to disclose information (Feuls et al., 2016). Confirming well-established characteristics of common user roles in our study may improve the generalizability of our findings on how users benefit in online peer groups depending on their user role.

Second, our study provides evidence that both low-contributors and high-contributors benefit from participation in online peer groups. In our online peer groups, we observe overall positive peer group effects regarding job search intensity and job search skills, i.e. success indicators predicting reemployment. At the same time, low-contributors and high-contributors develop at least as good as the control group with respect to any measured construct associated with reemployment chances. Likewise, prior research indicates that less active users (in some cases as much as active users) might benefit from participation in online communities (van Uden-Kraan et al., 2008a; Mo and Coulson, 2010). However, these findings only rely on one-time asking users about their perceived benefit (van Uden-Kraan et al., 2008a). In contrast, our research methodology allows to explicitly extract certain users’ benefit associated with participation by considering a control group (Klier et al., 2019). Thus, we are first to prove that users indeed benefit from participation (compared to non-participation) in online communities regardless of their role of contributing to the community.

Third, our findings indicate that low-contributors in online peer groups might benefit more than high-contributors in dimensions where they initially lag behind other users. In our study, low-contributors initially provide a lower level of number of applications (p<0.05) than high-contributors, significantly develop better (p<0.1), and thereby catch up. Still, they do not reach the high-contributors’ final level.
The related peer group effect in literature is positive behaviour change, for instance proven in the context of youth unemployment (Klier et al., 2019). Our results expand these insights and propose that low-contributors benefit even more by means of this peer group effect than high-contributors, which leads to a balancing effect within the group. Social comparison, a dynamic process observed within groups (Brown, 1988), might explain this interesting finding. Indeed, normative pressure to conform to the behaviour of others in the group can make people reappraise their own situation (Asch and Guetzkow, 1951). In our study, the initially less active users might be inspired by the lead of the highly contributing users and adjust their behaviour respectively.

Finally, our findings suggest that high-contributors in online peer groups benefit more from participation than low-contributors in terms of skill acquisition. High-contributors in our study acquire significantly more interview application skills than low-contributors (p<0.05) during participation and thus benefit more by means of increase of knowledge, a well-known peer group effect in literature (e.g. Niela-Vilén et al., 2014). High-contributors establish a lead in pertinent skills and at the same time are significantly more often invited to job interviews (p<0.001) than low-contributors during participation. We are the first to reveal that highly contributing users in online peer groups disproportionately benefit from knowledge acquisition, which constitutes a complex cognitive process. This is surprising at first glance, as in an open discussion, the entire content is visible to all users. Research on knowledge management found that multiple interactions between people in a group allow relational and cognitive aspects of relationships to emerge (Krackhardt, 1992), such as mutual knowledge (Krauss and Fussell, 1990). Strong relationships between people are seen as the backbone for collaboration (Watson and Papamarcos, 2002). To illustrate, Riemer et al. (2015) found that in enterprise social networks, users with strong relationships exhibit higher job performance than those without. In online peer groups, interactions are characterized by social support, which often addresses a single recipient, for instance through personal advice (Coulson et al., 2007). Recipients, who themselves contribute to the group, facilitate others in the group to get to know them and thus, to more effectively collaborate in solving their individual problems. Self-determination theory, which describes what sustains behaviour (Deci and Ryan, 2008), suggests reversed causality, i.e. competence gain in online communities sustains sharing behaviour (e.g. Yoon and Rolland, 2012; Zhang, 2016). Against the background of social exchange theory, which helps to understand what maintains relationships (Blau, 1964; Yoon and Rolland, 2012), our findings imply that high-contributors provide high commitment to the group due to their skill acquisition and are thus more likely to maintain their sharing behaviour (Jin et al., 2010).

Despite these theoretical insights, our findings indicate three practical implications for organizations and community managers. First, our study demonstrates that online peer groups are an effective instrument to support older unemployed people with their job search regardless of their behaviour contributing to the group. Indeed, both low-contributors and high-contributors benefit from participation in dimensions that predict reemployment. High-contributors reflect advanced or heavy users of digital media while low-contributors reflect digital sporadics or novices who use less digital media applications for their job search. Thus, organizations offering online peer groups to enhance reemployment chances should especially take effort to also motivate the digitally less active unemployed people for participation, as they also benefit. Second, community managers should install online peer groups with a heterogenous mix of digitally active and digitally less active unemployed people to induce activating effects for the less active unemployed people. While the presence of low-contributors does not impede high-contributors’ benefit, low-contributors participating in online peer groups particularly improve their job search intensity and digital competencies. Third, community managers can leverage the impact of online peer groups by maintaining and promoting user engagement. Our results suggest that high-contributors fulfil a dual role for the success of online peer groups. First, they contribute to the group by supporting others. Second, they particularly benefit themselves in terms of pertinent skill acquisition. To promote user engagement, community managers might on the one hand maintain high-contributors’ engagement and on the other hand encourage low-contributors to disclose information and thereby assist them to develop from a low-contributor to a high-contributor.
5.2 Limitations and future research

While our research presents first interesting insights, several limitations remain and might serve as starting points for future research. First, our results are based on one specific use case with limited online peer group data collected from a field experiment with one institution. However, as the data comprises multiple online peer groups instantiated at various employment agencies of the German Federal Employment Agency, we are confident that our rich dataset provides a solid foundation for the analysis in a very relevant context. Future research may analyse datasets from online peer groups in contexts other than unemployment to further validate our findings. Second, we only compared low-contributors and high-contributors as (static) user roles in our setting. In particular, we did not capture the dynamics of user roles. To illustrate, lurkers might develop to contributors and vice versa (Malinen, 2015). Nevertheless, we based the derivation of user roles on a solid foundation, i.e. users’ exchange of social support which represents their contribution to the group. We encourage researchers to investigate more complex user roles by incorporating personal data, discussed topics, and quality of contribution as well as other methodologies, such as social network analysis in a next step. Third, our data collection is based on measurement of constructs’ initial level and final level to determine users’ development. Future research might analyse users’ continuous development, for instance by means of “pulse check”-type surveys. Fourth, the analysis in this study focused on important but limited aspects of benefit from users’ perspectives, i.e. peer group effects that could be instantly assessed via surveys. Future research may expand these findings and analyse objectively measurable as well as long-term effects like for instance employment status. Fifth, our results do not constitute a final proof of causality between the users’ contribution of social support and their benefit from participation. In a next step, researchers might also consider measures from social exchange theory, such as commitment or self-determination theory, such as psychological needs to deepen our insights.

6 Conclusion

Online peer groups have enormous potential to create social value (Barak et al., 2008). Users in online peer groups may benefit by means of peer group effects and overcome a challenging situation or better deal with it (Felgenhauer et al., 2019b). The theoretical foundation of online peer groups is mutual social support (Coulson et al., 2007). Thus, actively contributing users are extraordinarily important for the groups’ success. Users’ contribution may be described by user roles (Malinen, 2015), which prior research found to be diverse. Research to date has neglected to investigate whether a user’s role of contributing social support is related to his/her benefit associated with participation.

To close this gap, in our study we quantitatively compared how users benefit from participation in online peer groups, depending on their role of contributing social support. We conducted our analysis using a unique online peer group dataset in the context of unemployment from a field experiment at the German Federal Employment Agency. To explore user roles, we used cluster analysis (Hacker and Riemer, 2020), based on users’ contribution in the form of seeking and providing social support (Coulson et al., 2007). Our focus was to statistically compare the extent how different users benefit from participation by means of peer group effects. Our results reveal that both low-contributors and high-contributors benefit from participation in online peer groups. Low-contributors benefit more than high-contributors in dimensions where they initially lag behind other users, in our context job search intensity. They catch up but do not pass the high-contributors’ level. High-contributors disproportionately benefit by acquiring pertinent skills and are thereby able to establish a lead over low-contributors. The contribution of our paper is twofold. We are the first to provide insights on how different users benefit from participation in online communities depending on their role of contributing social support. Moreover, we contribute to the understanding of the inner workings of online peer groups by quantitatively comparing how low-contributors and high-contributors benefit from participation by means of peer group effects. We hope that our findings will encourage future research in this fascinating field to study the inner workings of online communities thereby exploiting their societal value.
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