The Value of a Recommendation: The Role of Social Ties in Social Recommender Systems

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Abstract

In the past, the selection of content has been done manually. Nowadays, owing to the new generation of social recommender systems, the automated aggregation of content, based on social information from social networks, might become possible. Social ties provide information about the underlying structure of social networks. This information, integrated into a system, might affect a user's evaluation of a specific recommendation. However, there is no research about the integration of social ties and other determinants that could affect the value of a recommendation. We developed a research model and tested it in an online experiment using Facebook data for the use case of online news with 193 participants. The structural equation model results show that a strong tie relationship has positive influence on the value of a recommendation. The credibility of the recommending person and the recommendation's media source affect the value of a recommendation as well.

1. Introduction

Since the internet came into existence, the selection and bundling of content has traditionally been done manually and thus been exposed to human control. For instance, in the case of news, the selection of news was undertaken by a single or small group of journalists. It was the journalist's task to determine the relevant and most interesting content for all readers. This process has changed dramatically owing to the development of new information and communication technologies. News aggregators select the content without any manual interaction and prioritize it according to the wisdom of the crowd. An example is Google News, which automatically aggregates content from different sources. Different scholars have already examined this research field [e.g. 45].

Nowadays, owing to the development of Web 2.0, the amount of consumable and viewable content has also increased. As a solution, content selection might be carried out by the new generation of social recommender systems, which rely on social information from a social network (e.g. the social graph in Facebook). In this case, the aggregation of relevant news is performed automatically and adjusted to a user's individual preferences. Bakshy, Rosenn, Marlow, and Adamic [4] identify three different mechanisms to explain content diffusion in social networks: First, users can share a link in a social network, and friends might re-share the same link. Second, friends visit an external website and both share a link to this website in their feed. Third, a user shares a link outside a social network, prompting a friend to share the link in a social network. All three mechanisms show the relevance of sharing and recommending content and the increased impact of content received through interpersonal relationships in social networks.

Social recommender systems need information about people's relationships from a social network to function accordingly. The concept of social ties provides insights into a user's structural properties as well as the properties of single peers, first presented by Granovetter [22]. Social ties can be categorized into strong ties (e.g. trusted friends or family members) that share redundant information with a huge overlap. In contrast, weak ties (e.g. acquaintances) share more diverse and new information. This information can be used in social recommender systems to generate more specific recommendations, depending on what information the user desires [47]. Different scholars have shown that the use of social information in social recommender systems can improve the accuracy of a recommendation [2]. Therefore, these systems exhibit additional value, and a new and individualized consumption of content is possible.

Nevertheless, there is little research about social ties' impact on recommender systems in the information systems (IS) literature [2, 12] and none about other determinants' impact. Our study tries therefore to identify different determinants influencing the value of a recommendation for an individual user. Different scholars have already dealt with this,

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however, not in a sufficient manner [e.g. 27]. This is why we address the following research goals: First, we examine the importance of tie strength between the recommender and the recipient of a recommendation and its impact on the value of a recommendation. Second, we investigate the recommender's credibility and its impact on the value of a recommendation. Finally, we consider the credibility of the media source, which is frequently indicated in a recommendation, and its impact on the value of a recommendation. This information is crucial for the future development and diffusion of social recommender systems.

The paper is structured as follows: In Section 2, we present a review of related concepts on recommender systems and social ties theories. Section 3 introduces the development of our research model and the hypotheses. Section 4 outlines the methodological approach to measure the value of a recommendation. Section 5 contains the empirical results. In Section 6, we discuss findings, highlight implications, and present some study limitations.

2. Related concepts

2.1. Recommender systems

Personalization technologies such as recommender systems have been in existence since the introduction of the Tapestry system by Goldberg, Nichols, Oki, and Terry [21]. According to Montaner, López, and De La Rosa [40], they assist the user with providing structured information and with searching, sorting, and filtering the massive amount of online information. In turn, this helps minimize the problem of information overload. For a long time, recommender systems were only used for e-commerce (e.g. recommendation by amazon.com), but they are now also used for other digital products, such as news or music. All recommender system types process a user's explicit and implicit preferences as data inputs. Combined with the initial user profile, user's preferences build the basic information to select and recommend content. Adomavicius and Tuzhilin [1] conclude that content-based filters, collaborative filters, and hybrid filters are the traditional and most widely used systems.

In the case of content-based filtering, recommendations for certain items are chosen in terms of the correlation between item characteristics and user preferences [52]. Here, the selection of appropriate recommendations strongly depends on item properties that are of high importance to the user and thus have priority owing to higher weightings. In comparison, collaborative filter mechanisms focus on the profiles of users with equivalent tastes and preferences. If similar profiles are found, items liked by this person are recommended [1]. This procedure reflects the suggestion that people with same interests prefer the same things [44]. Burke [11] finds that hybrid filtering promises synergy effects by combining different approaches. It has also been shown that recommender systems have an overall impact on transforming the internet. Pathak, Garfinkel, Gopal, Venkatesan, and Yin [42] showed that recommender system strength has a positive effect on online sales. For online retailers, these systems help intensify the long tail phenomenon and replace traditional trade.

Social recommender systems present the next generation of filter mechanism technology. Nowadays, recommender systems consider all profiles to be equal. However, instead of treating user profiles equally, social recommender systems also account for the relationships between users [23]. Carmagnola, Vernero, and Grillo [12] note that available information from social networks (e.g. Facebook, Twitter, or LinkedIn) is used as additional input data to construct a user's neighborhood. Neto and Nowé [41] describe a social network's social graph as the primary data source on internet users' personal relationships. They find that the use of social graph data in recommender systems outperforms traditional recommender systems on the basis of three dimensions. Hence, social recommender systems can rely on information about a user's profile, user's friends' profiles, and the relationships between these friends [43]. Sinha and Swearingen [48] propose that the personal opinion of friends or acquaintances is the most efficient source of information. Li and Karahanna [35] have shown that these systems can recommend items, improve recommendations' selection and weighting, and increase recommendation accuracy. Arazy, Kumar, and Shapira [2] surveyed 116 participants and concluded that information from social "relatives" has stronger impacts owing to higher trust.

2.2. Social tie theories

Scholars have adopted social tie research as an analytic framework to analyze individuals and organizations and their behavior. Tie strength, which quantifies the characteristics between two nodes, has been under investigation by social network theories for some time. It was first introduced by Granovetter [22], who analyzed the interpersonal structure between two persons and divided relationship strength into three possible conditions: strong tie, weak tie, or absent tie. The latter refers to a lack of a relationship or ties, with a mere "nodding relationship" [22]. Interpersonal tie strength is a linear combination of the amount of time, emotional intensity, intimacy (mutual confiding) and reciprocal services that characterize each tie. Gilbert and Karahalios [20] add structural support, emotional support, and social distance as tie strength dimensions; the latter shows the strongest influence. Strong ties refer to a group of trusted friends or family members who share similar interests and high homogeneity in preferences and behavior. Weak ties encompass acquaintances who provide unique or fresh information and often exhibit highly heterogeneous behavior [20, 39]. Owing to the rise of social networks, researchers have sought to analyze social ties' impacts on the spread of information. Bakshy, Rosenn, Marlow, and Adamic [4] analyze the role of strong and weak ties in information propagation and show that strong ties are more influential at an individual level. They also note that weak ties play a more important role in the diffusion of online content than currently believed, since they share and diffuse new content and information. Bonhard and Sasse [7] conclude that users prefer the recommendations of friends and familiar persons so that it is more likely that users read and share such content. Koroleva and Štimac [33] reveal that Facebook users prefer getting information from their strong ties, at least if such information is not redundant due to network intersections between peers. In contrast, the results of Steffes and Burgee [49] show that weak ties are much more effective at influencing individuals' decision-making processes.

To use social graph information in social recommender systems, it is necessary to distinguish automatically between social ties in social networks. Gilbert and Karahalios [20] present a model using social media data to map different degrees of tie strength with high accuracy. Kahanda and Neville [28] use transactional events such as file transfer among peers in an online social network to differentiate between strong and weak ties. Farrow and Yuan [18] contribute to this research field by showing a highly positive impact of using online social networks on tie strength. Active usage enhanced communication intensity, emotional closeness and thus positively influenced participants' behavior and attitudes. Seth and Zhang [47] identify tie strength as a useful tool to structure the huge amount of data in online social networks. Based on this analysis, it is possible to draw conclusions about potentials of social relationships' in online search and recommendation systems.

3. Research model and hypothesis development

We seek to examine the *value of a recommendation* (VoR) and how it is influenced by different determinants. Due to the novelty of this approach, we understand and define the VoR as the accuracy of news recommendations for the recipient.

The development of our research model is theoretically justified on the uses and gratification approach, first mentioned by Katz, Blumler, and Gurevitch [29]. The main idea is that media provides a user with (new) information. On the one hand, the user has a certain expectation about the desired content. On the other hand, through the selection of the right content, he or she has an active role in reaching the highest satisfaction and accuracy level. After consumption, users feel either of high or low gratification, depending on the content's accuracy. This gratification leads to an expectation concerning media consumption in a user's next decisional situation in the future. The theory has been applied to IS research, it has extended knowledge of media attendance and explained behavior when using new technologies, such as cable television or personalized content services [34, 37]. In our case, the theory can be adopted as a framework for the accuracy of a recommendation in the decisional situation. Every recommendation from one user to another (from the recommender to the receiver) puts the recipient in a situation where he or she must choose and read the recommended content or not. This highlights the importance of the accuracy of a recommendation. Overall, it indicates that a user's evaluation, is dependent on the gratification of an information retrieval process [29, 37].

To date, scholars have analyzed recommendation accuracy depending on different attributes. Liang, Lai, and Ku [37] analyze recommendation accuracy based on the two indices *precision* and *recall*, as well as which personalization type matched a consumer's preference. Precision is indicated by the amount of recommended news articles that is relevant to a user, that is, the number of articles recommended and read in relation to the numbers recommended. Recall measures the number of relevant news articles, recommended to the user, that is, the number of articles recommended and read in relation to the total number read. Li and Karahanna [35] define recommendation accuracy as a reflection of the personalization quality and the extent to which a recommendation matches a consumer's preferences. We follow this definition. In summary, high accuracy of a recommendation infers a high value of a recommendation [32]. As noted, interpersonal relationships between people can be defined as strong or weak ties, that is, *tie strength* (TS) [22]. The accuracy of a recommendation from a person with a strong tie might be higher than from a weak tie [39]. Therefore, the value of a recommendation is influenced by the tie strength between the recommender and the recipient. Thus, hypothesis 1 is formulated:

H1: *TS has a positive influence on VoR.*

Besides tie strength, a recommendation's credibility is a crucial factor in content recommendation. Source credibility has an impact on a recommendation's accuracy [26]. It consists of two main elements that affect the credibility of the total information source: source bias (source trustworthiness) and source expertise (perceived competence) [9]. This is in line with Schweiger [46], who separated between media credibility (credibility of the medium) and source credibility (credibility of the primary source: in our case the recommender). We therefore posit that credibility has two aspects: *media credibility* (MC) and *recommender credibility* (RC).

In Hypothesis 2, media credibility will be consolidated. Media credibility research focuses on the distribution channel delivering the content from the creator to the recipient. Media credibility describes the credibility of the news source and the channel through which the content is distributed. As stated in Benlian, Titah, and Hess [6], media credibility is a determinant of both a communication message's and a recommendation's effectiveness. It has been shown that a source's credibility has a positive effect on the overall credibility of a recommendation [13]. Therefore, highly credible sources are more convincing than less credible sources [16, 51]. The higher the media credibility (i.e. the credibility of a website, newspaper, or well-known blog), the higher a recommendation's overall credibility should be. On the other hand, in the case of lower media source credibility (i.e. a lesser-known website or blog), a recommendation's total credibility will be lower [51]. In turn, this will affect the value of a recommendation. We hypothesize:

H2: *MC has a positive influence on VoR.*

Hypothesis 3 describes recommender credibility, that is, the credibility of the recommending person or communicator. As early authors, Hovland and Weiss [26] showed that a recommender's credibility might impact on a recommendation's credibility. To date, recommender credibility has described a communicator's expert opinion level in a specific area, as well as how trustworthy he or she is considered by the recipient [10]. It has been shown that a communicator can influence the processing of a message – in our case, the recommendation [31]. In short, recommender credibility reflects a recommender's experience, his or her familiarity with the recipient, and his or her trustworthiness in a specific area. Thus, we hypothesize:

H3: *RC has a positive influence on VoR.*

Hypothesis 4 describes the recommender credibility's influence on the value of a recommendation in terms of the underlying social relationship. From their qualitative study, Brown, Broderick, and Lee [9] concluded that users evaluate the credibility of online information in relation to the individual contributor of the information in a virtual environment. Besides, according to the finding of Bansal and Voyer [5], strong ties can positively impact a person's purchasing decision after receiving a recommendation via word of mouth. We therefore conclude that, the stronger the relationship between the recommender and the recipient, the higher the recommender's credibility should be. Recommender credibility should be positively influenced by tie strength. This can be summarized in the following hypothesis:

H4: *TS has a positive influence on RC.*

Figure 1 presents the research model and our hypotheses.

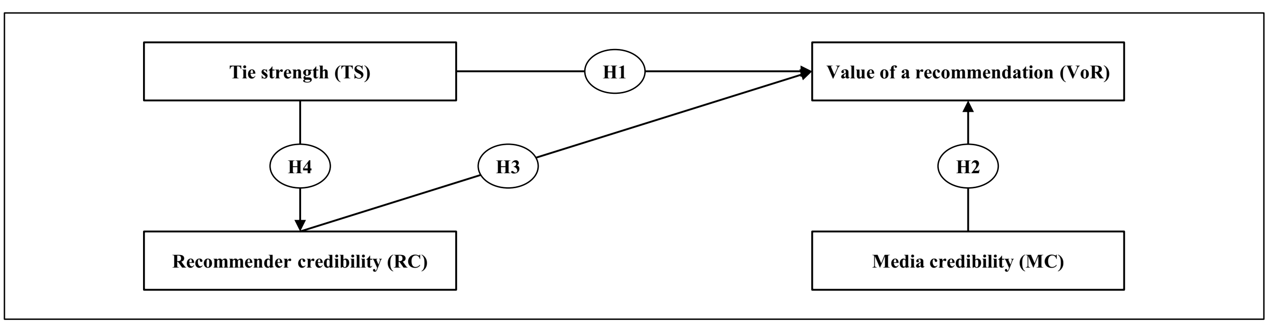

Figure 1. Research model and hypotheses

4. Research methodology

4.1. Measures

Whenever possible, validated constructs from existing research were used in the questionnaire. Extensive literature research was conducted in order to find useful and acceptable constructs. The survey was created in German. Therefore, we translated all items from English into German. We used the method of back-translation in order to verify the quality of the translation [8]. Also, minor wording changes were made to adapt them for the context of the underlying study. The measurement items for value of recommendation were adopted from Dooms, De Pessemier, and Martens [17]. Sample items include "the items recommended to me matched my interests" and "overall, I am satisfied with the recommender". The items for the social ties measurement were adopted from Marsden and Campbell [39] and Gilbert and Karahalios [20]. An example item is "how strong is your relationship with this person". To measure media credibility and recommender credibility, we adopted items from Dholakia and Sternthal [16]. All items were measured and rated on a 7-point Likert scale (where 1 refers to the lowest score and 7 to the highest score). All constructs were measured using a reflective measurement model.

4.2. Online experiment

To collect data and evaluate the research model with hypotheses, an online experiment including a quantitative standardized online survey was developed with the software Unipark by Globalpark.

The main challenge was to provide a reliable relationship between the recommender and the recipient in the experiment. For this, an innovative approach, using data of the social network Facebook, was chosen. Therefore, a Facebook application was implemented and integrated into the online experiment. By doing so, with user permission, the application was able to connect with Facebook via the application programming interface (API) to retrieve information about the participant. We did not save any data retrieved from Facebook and only integrated the information into the experiment. The social network provides information about friend lists so that it is possible to retrieve the interpersonal structure between a participant (receiver) and a randomly chosen recommender. The experimental setting is shown in Figure 2.

Figure 2. Experimental setting

The experiment was divided into three different parts:

1. Set-up of the social structure and credible topics.

2. Presentation of the recommendation.

3. Evaluation of the value of the recommendation.

First, following a short introduction, an explanation of the experiment's scope background, and data protection regulations, participants were asked to connect their Facebook account with the Facebook application *Umfrage zum Wert der Empfehlung*, which was developed exclusively for this experiment. Using this application, it was possible to access a user's basic personal information. These included Facebook ID, name, profile picture, friend lists, as well as friends' pictures. After successfully connecting to the application, a participant was presented with a randomly selected real friend's name and profile picture. The participant was then asked to evaluate the type of relationship to this particular person that is listed in his or her friends on Facebook. The participant was asked to evaluate the social tie relationship to the randomly chosen friend, who – in part 2 of this experiment – will recommend a pseudo-article. The participant was also asked to evaluate this person's recommender credibility concerning four different topics. Based on this, we could ensure to present a credible recommendation from the recommender in the experiment. To provide a broad spectrum, we chose the topics economy, science, technology, and culture, with a scale ranging from *not credible* to *credible*.

In part 2 of the experiment, an individual recommendation was presented to the participant. It consisted of a combination of an article preview and the previously evaluated friend's name and picture, as well as a randomly added media source. In total, eight media sources were implemented: four as highly credible sources (e.g. handelsblatt.de), and another four as less credible sources (e.g. bilanz-blog.de). We used extreme example in order to ensure that participants understood the differentiation between high and less credible sources [30]. The recommendation topic and teaser were chosen according to the credibility scores for the recommending person from part 1. Four different teaser topics were chosen from one online news source in order to ensure the same writing quality and style. All recommendations consisted of a headline and a short teaser text.

In part 3 of the experiment, the participant was asked to answer an online questionnaire in order to evaluate the presented recommendation and the value of the recommendation.

4.3. Data collection

Before we collected data, a pretest was conducted to ensure the functionality of the Facebook integration, the experiment procedure, and the questionnaire wording and structure. The selection of media sources and articles were also revalidated by the pretest, to ensure the same categorization. We sent an invitation link via email to 1,117 participants from a representative panel of German Facebook users. Within one week in September 2012, 193 participants completed the questionnaire. The participants' age ranged between 18 and 93. The average age was 36, 60% of the participants were male and 40% female. The sample comprised 16% students, 57% employees, 5% self-employed persons, and 22% others. The missing values in our data sheet were replaced with linear trend calculation. We also tested our data for a potential nonresponse bias and compared the answers of the last quarter of the participants with other participants' answers [3]. A t-test showed no significant difference between the two groups' mean answers. Also, we manually inspected all 193 observations. We concluded that a nonresponse bias was not present in this sample.

5. Results

We used structural equation modeling to analyze the collected data and test the hypotheses. The software SmartPLS 2.0 M3, using a partial least squares (PLS) algorithm, was used for the analysis. It has the advantage of modeling latent constructs and predictive models that are usable for small sample sizes [14]. The algorithm minimizes residual variances in order to enhance the model's predictive power [14]. Due to PLS estimations performed by iterations of regressions, no sample distribution assumption was necessary [38]. It has been shown in the past that this approach is highly appropriate for explorative studies as ours [24]. We used SmartPLS to calculate coefficients and to determine the path significances by using the bootstrapping algorithm. To analyze the model's quality, all values had to be above literature-based thresholds to provide a valid model by assessing the Cronbach's α, composite reliability, average variance extracted (AVE), and discriminant validity [25]. All items had Cronbach's α values above the threshold of .70 and showed content validity [25]. Also, composite reliability showed values above .70 in all cases [14]. Furthermore, the average variance extracted (AVE) showed values above the threshold of .50 [14]. Finally, discriminant validity was analyzed by comparing the latent construct correlation and the square root of the specific AVE. In all cases, the AVE's value was higher than the square root, and therefore provided discriminant validity [19]. In short, all constructs satisfied reliability and validity criteria. Table 1 provides an overview of the results.

Table 1. Factor loadings, composite reliabilities, AVEs, and Cronbach's α

Construct	Item	Standardized factor loadings	Composite reliability	AVE	Cronbach's α
VoR	VoR_1	.875	.963	.811	.953
	VoR_2	.882			
	VoR_3	.950			
	VoR_4	.904			
	VoR_5	.876			
	VoR_6	.916			

TS	TS_1	.897	.828	.618	.703
	TS_2	.747			
	TS_3	.703			
MC	MC_1	.959	.959	.922	.915
	MC_2	.961			
RC	RC_1	.931	.969	.886	.957
	RC_2	.949			
	RC_3	.934			
	RC_4	.951			

We followed the approach of Liang, Saraf, Hu, and Xue [36] to analyze a potential common method bias. Using SmartPLS, we added a method factor to the original latent variables (defined as substantive factors) in the research model. We then calculated squared factor loadings for both factors: method factor and substantive factors. The average variance explained by the substantive factors was about .84, the method factor variance being under .01. These results suggest that a common method bias should not be a concern in this study.

To analyze our structural model's validity, we calculated Q² as the indicator for predictive relevance, based on the blindfolding procedure. We followed the cross-validation technique of Stone [50]. By convention, $Q^2 > 0$ suggests predictive model relevance, whereas $Q^2 \leq 0$ suggests a lack of relevance. In our model, all constructs had a positive Q², indicating that we have predictive relevance [19, 50]. We analyzed Cohen's f² to determine each path's effect size. Based on the literature, a value of .02 indicated a small, a value of .15 a medium, and a value of .35 a large effect size [15]. All our results showed at least small effect sizes.

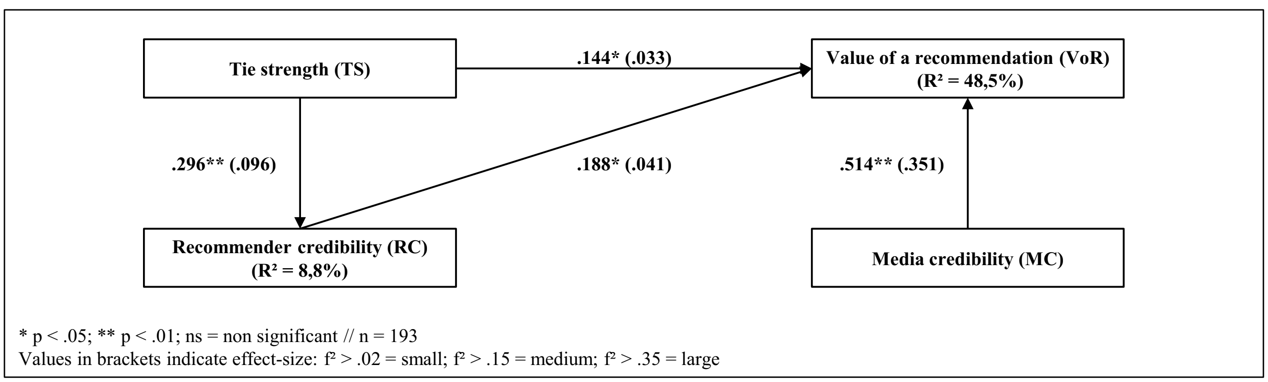

Figure 3. Structural equation model results

As shown in Figure 3, our three main constructs were able to explain 48.5% of the variance in the value of a recommendation ($R^2 = .485$). Also, variance in RC was explained with a R^2 of .088. Our results showed that TS had a significant, positive effect on VoR: The stronger the relationship, between the recommender and the recipient, the higher the value of a recommendation. Therefore, we were able to support H1 ($\beta = .144$, $p < .05$). We also found support for H2, whereas MC positively influenced VoR ($\beta = .514$, $p < .01$). Also, RC positively influenced VoR ($\beta = .188$, $p < .05$), supporting H3. Finally, TS had a significant and positive effect on RC ($\beta = .296$, $p < .01$), which supported Hypothesis H4. A summary of the results can be found in Table 2.

Table 2. Results

Hypothesis	Effect	t-value	Result
$H1^+$	TS → VoR	2.222	Supported
$H2^+$	MC→ VoR	6.975	Supported
$H3^+$	RC → VoR	2.200	Supported
$H4^+$	TS → RC	4.349	Supported

6. Conclusion, implications, and limitations

The study's main goal was to investigate determinants affecting the value of a recommendation. We defined the latter as the accuracy of a recommendation in the application domain of online news. A key element of social recommender systems is the integration of social information, for instance the social relationship between the recommender and receiver of a recommendation. The theory of social ties gives insights in the structural relation of a user and is therefore crucial for social recommender systems. First, we explored the value of a recommendation, affected by the tie strength between the recommender and the recipient. Second, the effect of the credibility of the recommending person and the recommendation's media source on the value of the recommendation should be identified in the study.

The results of an online experiment with 193 participants showed that a recommendation is of higher value if a news article is recommended by a strong tie (i.e. a close friend or a family member). We could show that, if an article is recommended by a strong tie, there is a higher interest in the article. Also, recipients would rather read the whole article (not only the teaser text) and recommend the article to others. These results reveal social connection's relevance in the recommendation process. We could also show that a recommended article's media source affected the value. The higher the media source's credibility was, the higher the value of the recommendation. Also, higher recommender credibility led to higher value of a recommendation. This leads to the assumption that closely related people in a user's social network provide a high credibly on certain topics. In summary, the integration of highly credible sources in the recommendation has an overall positive effect.

Our results showed that the social ties relationship affects the recommender's credibility. The stronger a relationship's tie was, the higher the recommender credibility. Mostly, if the person is a weak tie, it is hard to consider his or her credibility on certain topics. This might be a reason for the lower explanation of the variance in recommender credibility. We could also show that articles the recipient was familiar with were mostly recommended by strong ties. In turn, this implies that new articles would rather be recommended by weak ties.

Considering these results, we contributed to the research field of social recommender systems. We provided information about these new systems' impact: Social recommender systems should incorporate social tie information in the algorithm and display it with the recommendation. Thus, these results also drive the discussion about the transparency of the technology's functionality in a new direction. By using this new generation of social recommender systems, the aggregation of news is performed automatically. Furthermore, a first approach is already implemented in practice. A new type of service, Personalized News Aggregators (PNAs), presents an automated selection and bundling of relevant news from different sources, adapted to an individual user's preferences. PNA developers can rely on our findings and can provide a more accurate selection of news articles to every user. Mostly, PNAs are connected to a user's social network (e.g. with the Facebook login) and could therefore easily use profile and social information. This would improve the selection of the right content. As PNAs might provide the requirements to establish a new business model for news, information about underlying recommender systems is crucial. If a system could automatically recommend relevant and interesting articles for a user, this might lead to a higher willingness-to-pay.

We also contributed to social network research. We created an appropriate research model in order to measure the value of a recommendation and its influence by social information. We also showed how to integrate real Facebook data by using the Facebook API to measure social tie relations. Our three key constructs explained nearly half of the total variance in the value of recommendations. In total, the existence of social information in the internet will increase in the future. Therefore, we provided a theoretical template to derive implications about incorporating social information in personalization technologies.

This study also has some limitations: First, we only considered the value of a recommendation and defined it as the accuracy of a recommendation. We did not separately consider the acceptance of a recommendation. In order to properly evaluate the value of a recommendation, future studies should first consider the acceptance of a recommendation, in order to control if the recipient is clicking on the recommendation or not. Only if the user accepted the recommendation it is possible to assess the accuracy of the recommendation. Second, the implementation of our online experiment has some limitations. The evaluation of the relationship is only self-reported and might lead to a potential social desirability bias. Also, the pre-selection of the news articles and media sources might bias the results. The evaluation of credibility might also bias the design. Our procedure should be developed further to extend the evaluation of friends, the selection of news and sources. An experimental setting, whereas the evaluation of the social ties and the evaluation of the recommendation will be separated, might provide further insights. Third, we addressed three key constructs in the research model which explained almost half of the variance in the value of a recommendation. However, future studies should explore other variables, as well as moderating effects to help draw a more complete picture of recommendations. Fourth, we only presented one recommendation to our participants. According to the uses & gratification approach, the behavior might change with a longer use of the system. Also, feedback (e.g. accuracy) about the first recommendation should be included in the presentation of a following recommendation. Thus, future research should present every participant with several recommendations.

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