An Application of UTAUT2 on Social Recommender Systems: Incorporating Social Information for Performance Expectancy

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Abstract

The recently proposed extended Unified Theory of Acceptance and Use of Technology (UTAUT2) offers new opportunities for exploring the acceptance of consumer technologies. This study utilizes UTAUT2 to explore the user acceptance of social recommender systems that have become more attractive owing to improved content personalization and adaptation to user preferences. Scholars have shown that these systems could improve a recommendation's accuracy. However, the UTAUT2's applicability and the explanation of performance expectancy for social recommender systems are still unclear. We developed a UTAUT2-based framework and tested it in a quantitative study with 266 participants. The structural equation model results show that UTAUT2 is applicable in the context of social recommender systems. Furthermore, the user's social network information, profile information, and reading behavior positively influence performance expectancy and the intention to adopt a social recommender system. Therefore, incorporating social information might overcome the shortcomings of other classic recommender systems.

1. Introduction

Recommender systems have been used since the beginning of e-commerce and are seeing wide application. Besides physical products, digital products such as news or music can also be recommended. Recommender systems can elicit the interests or preferences of individual users, either explicitly and/or implicitly, and can make recommendations accordingly [46]. Due to the great success and strong development of social networks (e.g. Facebook) in the past few years, new opportunities have emerged for recommender systems design: so-called social recommender systems draw on information from a user's social network [25]. Through the use of this information, a new way to improve the selection and weighting of recommendations has become possible. This increases the recommendation accuracy, and enables a new consumption of content owning to the adaptation to a user's preferences [2]. As a result, this might minimize the problem of information overload – as the high volume of news available online – and allows for an automated bundling of content. Therefore, the application domain of social recommender systems in this study is for online news. To date, there is extensive research about the (technical) design of different recommender system variants, but very little about social recommender systems [e.g. 2, 34].

Technology acceptance research traditionally had a strong focus on professional users in the corporate environment. Models such as the Technology Acceptance Model (TAM) or the original Unified Theory of Acceptance and Use of Technology (UTAUT) explicitly omitted factors such as hedonic motivation, making them inappropriate for applications in the consumer context [9, 43]. With the recently proposed UTAUT2, technology acceptance research finally has access to a consolidated tool to explore consumers' adoption behavior [44].

There is little research about the exploration of user adoption and experience of recommender systems by using TAM or UTAUT [e.g. 24, 45]. However, besides the authors' original study on the adoption of mobile internet in Hong Kong, there are very few empirical applications of UTAUT2 in other contexts. Therefore, this study first examines UTAUT2's applicability in the new context of social recommender systems. Next to the exploration of the underlying technology and algorithms of social recommender systems, scientific research of user adoption has also become an interesting field of research and gives implications for future business models. The UTAUT2 construct of performance expectancy describes the relative advantage of a technology, and is therefore central to this investigation. Hence, we extend the construct by means of three newly developed constructs in the

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context of social recommender systems. We want to show whether or not there are general advantages in the use of social recommender systems.

The remainder of this paper is structured as follows: The section 2 reviews the relevant literature on recommender systems, social recommender systems, and technology acceptance. Based on this overview, in section 3 we develop a research model of user acceptance for social recommender systems and formulate hypotheses. Section 4 outlines the methodological approach to test the derived hypotheses. In section 5, we present the main findings of our statistical analysis. Finally, in Section 6, we discuss findings, derive implications, and conclude with some study limitations.

2. Relevant literature

2.1. Recommender systems

Personalization technologies such as recommender systems have been in existence since the introduction of the first system, Tapestry, by Goldberg, Nichols, Oki, and Terry [16]. These technologies assist a user by supplying well-structured information in searching, sorting, and filtering the huge amount of information available online [29]. The most traditional and widely used technologies are content-based filters, collaborative filters, and hybrid filters [1]. These are also known as classic recommender systems [31].

Content-based filters recommend items to users based on the item's description and a profile of the user's interests [32]. They analyze the content of text information and match it with the elicited user preferences [40]. Thus, a content-based filter is characterized as a recommender system that employs information about the user and the content in order to generate recommendations. Instead, collaborative filters recommend items to users that other users with similar tastes have liked in the past [34]. This builds a database of user preferences for items. Every user is matched against the database to discover neighbors – other users with a similar taste to the new user. Items liked by these neighbors are then recommended to the user because he or she might also like them [37]. Thus, a collaborative filter requires no information about the content itself, but instead uses information about the user and other users in the system to generate recommendations. The information about the user's association with other users is thereby inferred by the recommender system itself. Finally, hybrid filters combine both approaches and achieve powerful synergies [6].

With the rise of Web 2.0, social networks and social information have become public, for instance via the social network Facebook. Therefore, a social recommender system can recommend items based on the preferences and information from a user's social network. For instance, it can draw on information about the user's friends' profiles and the relationships between friends in the social network [34].

One of the central theoretical concepts for social recommender systems is social network analysis, which offers measures to assess the properties of peers, the properties of ties between peers, and a network's overall structural properties [41]. The findings by Granovetter [17], for example, suggest that strong ties (e.g. a group of trusted friends or family members) share redundant information, while weak ties (e.g. acquaintances) share more diverse information. Bakshy, Rosenn, Marlow, and Adamic [3] analyzed the role of strong or weak ties in information propagation in the context of Facebook. They found that strong ties are more influential on a personal level, and showed that weak ties play a more important role in the diffusion of new content. Transferred to a social recommender system, this means that a recommender system can utilize strength and distance information to generate accurate recommendations. Social recommender systems thus analyze a user's relationships to other users and calculate the social distance between users by traversing the underlying social network's graph. Sinha and Swearingen [38] propose that the most efficient source of information for a decision comes from the opinions of friends, acquaintances, or friends of friends. Also, these people present the highest power in influencing a user during a decision. In conclusion, users might value recommendations more if they are based on their own social network than on other anonymous users (collaborative filter) or an automatic algorithm (content-based filter). Several studies have shown that social recommender systems can outperform classic recommender systems in terms of accuracy [18, 19, 25]. Social recommender systems can also overcome the new user problem, a major disadvantage of classic recommender systems [28]. However, social recommender systems also have some disadvantages. One downturn of a social recommender system might be a loss of diversity in recommendations if these recommendations are solely based on direct friends. Compared to direct friends' recommendations, Sinha and Swearingen [38] argue that an efficient and reasonable recommendation should also include anonymous and public opinions.

2.2. Technology acceptance

Technology acceptance research explores the determinants of individuals' adoption of (information) technology. The technology acceptance literature stream is founded on psychology research and goes back to the Theory of Reasoned Action (TRA) of Fishbein and Ajzen [12]. It argues that an individual's behavioral intention to perform a certain action is the result of his or her attitude towards this behavior and his or her subjective norms. In turn, behavioral intention leads to de facto behavior, which means that the individual performs the action. This theory is not limited to a certain domain of behavior, but aims to explain human behavior in general. Grounded in TRA [12], Davis [9] developed TAM with the goal of explaining managers' acceptance of new information technologies in the corporate environment. In this case, the attitude to using a technology depends on the technology's perceived usefulness and perceived ease of use.

Since then, a broad literature stream has both applied and modified this approach several times. But, as a result, it became unclear which model is most appropriate for a certain scenario of technology acceptance. Based on this, Venkatesh, Morris, Davis, and Davis [43] evaluated existing technology acceptance theories and developed UTAUT, according to which, technology usage behavior depends on behavioral intention, which in turn depends on the four factors performance expectancy, effort expectancy, social influence, and facilitating conditions. Technology acceptance research, including UTAUT, have to date mainly focused on the professional environment, considering only extrinsic motivations for information technology use [43]. However, such theories are insufficient to appropriately explain a consumer's information technology adoption, because the situation, environment, and technology differ from the corporate context. To address these shortcomings, Venkatesh, Thong, and Xu [44] developed UTAUT2, including three new constructs: hedonic motivation, price value, and habit.

3. Research model and hypothesis development

Our research framework provides the theoretical basis for explaining how different technical characteristics of a social recommender system lead to the adoption for news personalization. For this purpose, this study adopts UTAUT2, in order to provide a theoretical framework to analyze a technology's adoption. It thereby follows the work of Venkatesh and Davis [42], and explores the external variables as determinants of *usage behavior* (UB) for a social recommender system. In particular, it explores social recommender system characteristics as external variables of UTAUT2. This research on information system characteristics as an indication of technology acceptance has been validated [e.g. 10, 23, 45].

Because there is as yet no proposed social recommender system for news, this framework does not seek to explain de facto UB. Instead, it seeks to explain the *behavioral intention* (BI) to use, which we utilize as a reliable indicator predictor for future UB. Validated by different scholars, it is therefore satisfactory to explain only BI [e.g. 12]. Following Venkatesh, Thong, and Xu [44], *performance expectancy* (PE) is defined as the "degree to which using a technology will provide benefits to the consumers in performing certain activities." In the case of the proposed social recommender system, one element of the PE – relative advantage – is particularly important. A social recommender system has the technical advantage that bundling content (in particular) can be transformed from manual bundling to automated aggregation. Therefore, PE captures the absolute benefit for the user as well as the relative advantage of the technology compared to other, preceding technologies [36]. The latter is of particular interest in this study, because the inclusion of social information in a recommender system might explain the relative advantage over existing recommender systems. Thus, we hypothesize:

H1a: *PE has a positive influence on the BI to adopt a social recommender system.*

In order to apply the complete UTAUT2 model in the context of social recommender systems, we included all remaining key constructs: *effort expectancy* (EE), *social influence* (SI), *facilitating conditions* (FC), *hedonic motivation* (HM), *price value* (PV), and *habit* (HB). Following Venkatesh, Thong, and Xu [44], we formulate the following hypotheses:

H1b: *EE has a positive influence on the BI to adopt a social recommender system.*

H1c: *SI has a positive influence on the BI to adopt a social recommender system.*

H1d: *FC has a positive influence on the BI to adopt a social recommender system.*

H1e: *HM has a positive influence on the BI to adopt a social recommender system.*

H1f: *PV has a positive influence on the BI to adopt a social recommender system.*

H1g: *HB has a positive influence on the BI to adopt a social recommender system.*

The development of this framework was supported by, first, a systematic literature review and, second, a qualitative study. Based on a review of about 80 recommender systems and social recommender systems articles, three central and relevant characteristics were identified for this framework.

To ensure the user relevance of the characteristics for the application scenario of news, 12 individual semi-structured interviews were conducted with technology experts, such as employees, bloggers, and journalists. This was necessary, because these system characteristics were only derived theoretically from the existing literature, which has a strong technical perspective. Furthermore, many applications of recommender systems are only implemented in the e-commerce domain, but not for content. Thus, it had to be evaluated whether or not the transfer of the identified characteristics to the news recommender domain was appropriate. The results confirmed the relevance of the derived system characteristics and thus the appropriateness of the transfer from the existing literature to the proposed scenario. The following characteristics are the result: *user's social network* (USN), *user's profile information* (UPI), and *user's reading behavior* (URB). In this case, user acceptance or non-acceptance of each of these characteristics should provide the basis for the design and implementation of a social recommender system.

Hypothesis 2 describes the use of social information in a social recommender system. Employing information from the user's social network to generate recommendations is the key function of a social recommender system [25]. Information about the social graph represents social data in a graphical way of a group of various users and allows the construction of a user's neighborhood. This information can be collected by several techniques from activities in a social network [11]. It allows studying relationships between users, in order to determine social metrics such as social distance [30]. These social approaches are based on the social distance between user profiles in the social network. They use information about the relationships and preferences of other, similar users (e.g. friends). Thus, we hypothesize:

H2: *Considering the USN has a positive influence on the PE of a social recommender system.*

In Hypothesis 3, the user's profile information will be consolidated. A core functionality of content-based filters is to utilize the information the user has actively entered, for instance, upon sign-up for the recommender system [29]. In social networks, users provide more information and more accurately, by choice. Typical examples of such profile information are the user's name, gender, age, and statements about his or her interests. This information can be used to improve the recommendation. Thus, the following hypothesis is formulated:

H3: *Considering the UPI has a positive influence on the PE of a social recommender system.*

Finally, Hypothesis 4 describes the use of information about the user's reading behavior in a social network and in the social recommender system. The functionality of a content-based filter can be transferred to a social recommender system. The observation of the user's reading behavior will therefore collect data for generating news recommendations. This data can include information about what the user has read in the past, how much time he or she has spent on individual articles, and which recommendations the user has accepted or declined in the past [29]. We hypothesize:

H4: *Considering the URB has a positive influence on the PE of a social recommender system.*

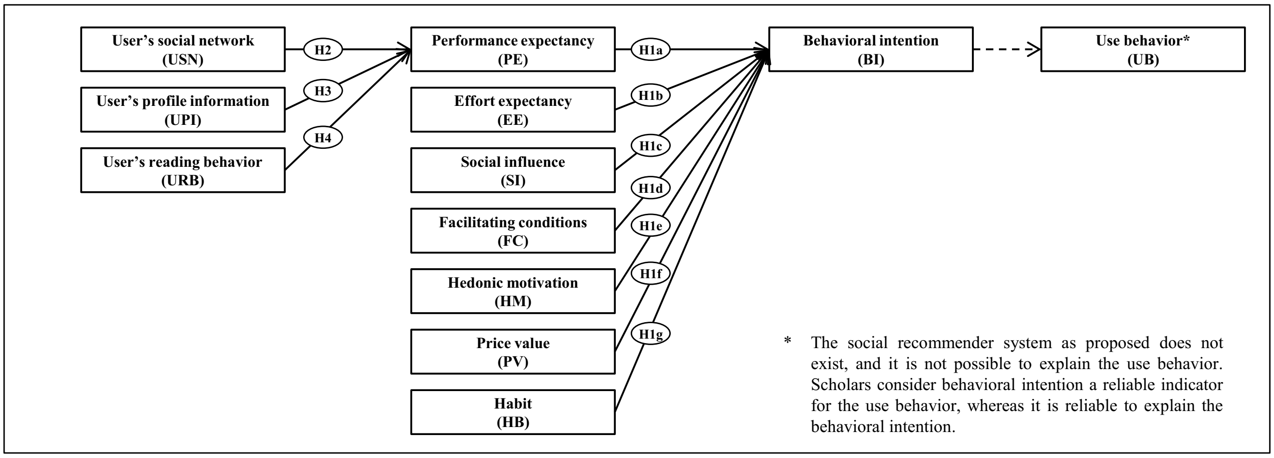


Figure 1. Research model and hypotheses

4. Research methodology

4.1. Measures

Where possible, we adopted measurement scales from existing research. Items of the original UTAUT2 constructs were adopted from Venkatesh, Thong, and Xu [44]. Owing to the focus of the integration of characteristics of social recommender systems, we used single-item measures for the UTAUT constructs SI, FC, HM, PV, and HB. Different authors have shown that there is no difference in the predictive validity of multiple-item and single-item measurement [e.g. 5]. Minor changes in the wording were made to adapt the questions to the scenario. PV could not be adopted and was measured by willingness to pay. The measurement items for the constructs USN, UPI, and URB were derived from the theoretical literature on recommender systems. In addition to an extensive study of the literature, these newly developed items were evaluated with the insights from a preliminary qualitative study. We applied the framework of Mackenzie, Podsakoff, and Podsakoff [27] for the development of these valid measures. Constructs and items can be seen in Table 1. Except for UPI, which was measured on a nominal scale, 7-point Likert scales (where 1 refers the lowest score and 7 the highest score) were used. All constructs were measured using a reflective measurement model.

4.2. Data collection

The data for this quantitative empirical study was collected using a standardized online questionnaire. At the beginning of the survey, a short video explaining the core functionality of social recommender systems in the context of news personalization was shown. The questions followed. This ensured that all participants had the same knowledge base. Moreover, a pretest was conducted to identify potential shortcomings in the questionnaire. The survey was developed with the Software Unipark by Globalpark and was conducted between June and August 2012. An invitation email was sent to 4,208 students of a German university. We followed the approach of asking a student sample in this early research development stage. This procedure is validated in similar cases and seems appropriate [4, 15]. Overall, 266 participants completed the questionnaire. The average age was 28, 137 participants were female and 129 male, and 255 subjects had at least a two-year college or equivalent degree. Most subjects indicated that they were smartphone and/or tablet users.

To identify a potential nonresponse bias, early and late observations were compared. A t-test provided no indication for the presence of a nonresponse bias at the level of 99.9%. Furthermore, a manual inspection of the 266 answer sets showed no indication of inconsistent answer behavior. Therefore, no observations were dropped from the dataset. To address the common method bias, we conducted Harman's single-factor test. More than one factor emerged from the analysis, and the first factor explained only 25.2% of the total variance. These results suggest that the common method bias should not be a concern in this study [33].

Table 1. Constructs and items

Construct		Item
USN	USN_1	Such a recommender system should take information from my social network (e.g. Facebook, Twitter) into account.
	USN_2	Such a recommender system should take into account, what my friends and my friends' friends from my social network read.
	USN_3	I want to recommend articles directly to my social network friends. *
	USN_4	I want recommendations from social network friends who are nearby.
	USN_5	I want recommendations from social network friends with whom I interact a lot. *
	USN_6	I want recommendations from social network friends with whom I interact little.
UPI	UPI_1	I would like to sign in to the recommender system and… (…) enter my name. *
	UPI_2	(…) enter my gender.
	UPI_3	(…) enter my age.
	UPI_4	(…) enter my city.
	UPI_5	(…) select my interests from a catalogue.
URB	URB_1	Such a recommender system should take into account what I have already read.
	URB_2	Such a recommender system should take into account how much time I have spent on individual articles.
	URB_3	Such a recommender system should take into account which recommendations I have accepted or declined so far.
	URB_4	Such a recommender system should take into account how I have rated individual articles.
* Deleted from construct due to low factor loadings.		

5. Results

The collected data was analyzed using structural equation modeling to test the proposed hypotheses. The software SmartPLS 2.0 M3, using the partial-least-squares (PLS) algorithm, was used for this analysis [35]. It has the advantage of modeling latent constructs and predictive models, is usable with small sample sizes, and is highly appropriate for our explorative study [7, 20]. To enhance predictive power, the algorithm minimizes residual variances [7, 14]. Therefore, no further sample distribution assumptions is necessary, because PLS estimation is performed by iterations of regression [26]. In this case, the software was used to calculate path coefficients and to determine the paths' significance in the model using the bootstrapping function.

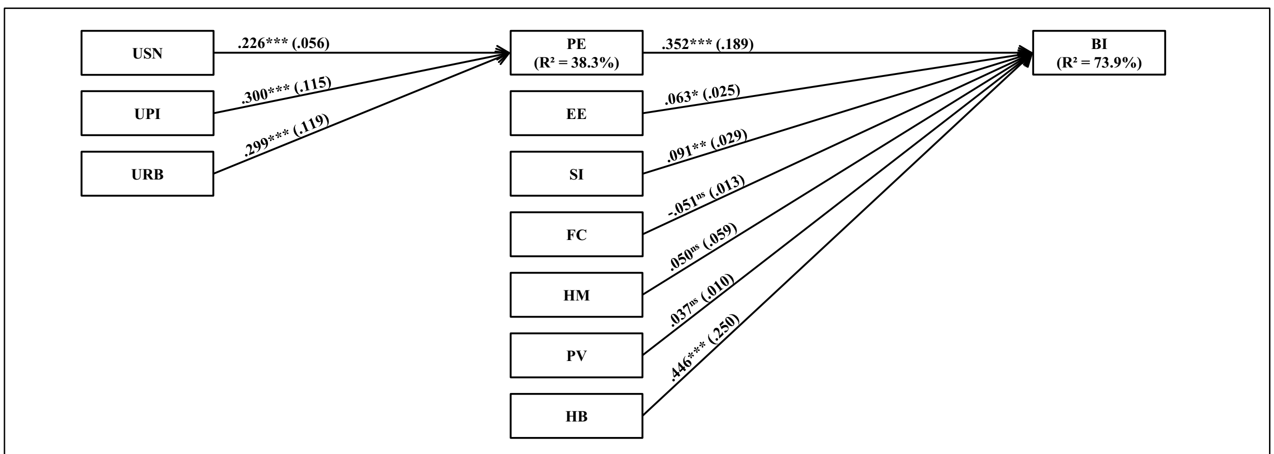
To provide a valid and high quality model, all values have to be above literature-based thresholds. Construct reliability and validity was assessed based on their respective Cronbach's α, their composite reliability, their average variance extracted (AVE), and their discriminant validity [22]. To establish content validity, all indicators must have Cronbach's α value above .70 [21]. For USN, two indicators, and for UPI one indicator were rejected. A new calculation of the model showed significant values above the threshold. Construct reliability is given if constructs have values above the critical value of .70 [7]. The composite reliabilities for all constructs are larger than .80. AVE for all constructs show values significantly above the threshold value of .50 [7]. Discriminant validity was examined by the investigation of the square root of the specific AVE and the latent construct correlation. For all constructs, the AVE's square root was higher than the correlation of the specific construct with any other construct in the model [13]. In conclusion, all constructs satisfied reliability and validity criteria. Table 2 provides an overview of the results.

Table 2. Factor loadings, composite reliabilities, and AVEs

Construct	Item	Stand. factor loadings	Composite reliability	AVE
BI	BI_1	.973	.972	.945
	BI_2	.971		
PE	PE_1	.855	.928	.721
	PE_2	.773		
	PE_3	.845		
	PE_4	.873		
	PE_5	.896		

EE	EE_1	.829	.927	.810
	EE_2	.932		
	EE_3	.935		
USN	USN_1	.841	.883	.654
	USN_2	.857		
	USN_4	.732		
	USN_6	.797		
UPI	UPI_2	.777	.822	.539
	UPI_3	.814		
	UPI_4	.756		
	UPI_5	.564		
URB	URB_1	.848	.903	.701
	URB_2	.720		
	URB_3	.899		
	URB_4	.870		
Due to single item measurement, not all items were reported.				

To analyze our structural model's validity, we considered Q^2 and Cohen's effect sizes f^2. We followed the approach of Stone [39] and calculated Q^2 as indicator for predictive relevance, based on the blindfolding procedure. Thus, $Q^2 > 0$ indicates a predictive relevance of the model, whereas $Q^2 \leq 0$ presents a lack of relevance. In our model, all constructs have a positive Q^2, indicating that we have predictive relevance [13]. We analyzed Cohen's f^2 to determine the effect size of each construct. A value of .02 indicates a small, a value of .15 a medium, and a value of .35 a large effect size [8]. All our significant results showed at least a small effect size. Figure 2 provides the results.



* p < .10; ** p < .05; *** p < .01 ; ns = non significant // n = 266
Values in brackets indicate effect-size: $f^2 > .02$ = small; $f^2 > .15$ = medium; $f^2 > .35$ = large

Figure 2. Results of the structural equation model

Overall, our three main constructs can explain more than one-third of the variance in PE ($R^2 = .383$). Also, variance in BI can be explained with a R^2 of 73,9%. As expected, for the first part of the results, PE has a significant, positive effect on the BI to adopt a social recommender system, supporting H1a ($\beta = .352$, $p < .01$). We found support for H1b, H1c, and H1g, whereas EE, SI, and HB positively influence the BI ($\beta = .063$, $p < .10$ / $\beta = .091$, $p < .05$ / $\beta = .446$, $p < .01$). FC shows a non significant influence on BI ($\beta = -.051$, $p > .10$) and a negative relationship, leading us to reject Hypothesis H1d. Finally, H1e and H1f can also not be supported ($\beta = .050$, $p > .10$ / $\beta = .037$, $p > .10$). Therefore, HM and PV do not lead to a higher BI. We also considered moderating effects of age, gender, and experience, but found not differences in the results.

Considering the second part of the results, USN, UPI, and URB were all found to have a significant and positive effect on PE ($\beta = .226$, $p < .01$ / $\beta = .300$, $p < .01$ / $\beta = .299$, $p < .01$). This supports Hypotheses H2, H3, and H4. A summary of the results can be found in Table 3.

Table 3. Summary

Hypothesis	Effect	t-value	Result
H1a+	PE → BI	5.180	Supported
H1b+	EE → BI	1.749	Supported
H1c+	SI → BI	2.067	Supported
H1d+	FC → BI	1.517	Not supported
H1e+	HM → BI	1.129	Not supported
H1f+	PV → BI	1.378	Not supported
H1g+	HB → BI	6.297	Supported
H2+	USN → PE	4.209	Supported
H3+	UPI → PE	4.760	Supported
H4+	URB → PE	5.035	Supported

6. Conclusion, implications, and limitations

This study sought to explore UTAUT2's applicability and the explanation of performance expectancy in the context of social recommender systems. It helps to explore user acceptance and to show the importance and advantage of including social information in recommender systems – the new generation of social recommender systems.

The results of a survey with 266 participants showed that users prefer a system that provides recommendations based on a combination of user's social networking information, profile information, and reading behavior. These characteristics are mainly included in social recommender systems and indicate a relative advantage in comparison to classic recommender systems. We could show that the integration of information from the user's social network could improve the intention to use such a system. As users prefer recommendations from well-know and trustworthy people, including this information could improve the automated aggregation of content. We could also show that the personal information, stated in the social network (e.g. gender or interests) leads to a higher intention to use and should be integrated in social recommender systems. Also, reading behaviors of users, which will be automatically generated by the social network, increase the intention to use and might improve the overall performance of the system. Furthermore, users consider the reduction of daily information overload to be a primary benefit of social recommender systems. A combination of these characteristics in recommender systems has the potential to achieve synergies, since the strengths and weaknesses of different recommender systems are often complementary. Particularly in the news domain, the quality of recommendations might suffer severely from the (still) limited capabilities concerning text analysis if they are solely derived by means of a classic recommender system. A social recommender system might be advantageous here, because it can utilize the collective human intelligence of a user's social network. Also compared to a classic recommender system, a social recommender system user could even self-select the people that he or she would like to receive prioritized recommendations from.

From a theoretical perspective, we have shown how UTAUT2 can be used to explore an application system's technical characteristics. For the particular case of acceptance for social recommender systems, we have applied and extended UTAUT2 with three theoretical new constructs. Our three constructs could explain more than one-third of the total variance in performance expectancy. This investigation provides future research with an appropriate theoretical template to get more information about the application and adoption of social recommender systems.

From a practical perspective, this study's findings might be helpful for publishing companies in transition from the traditional print era to the digital era. Because personalized content is potentially more valuable to a reader than a standard offering, it can increase readers' willingness to pay and, as a result, publishers' revenues. Therefore, knowledge about the underlying technology as well as user acceptance of this technology is crucial to leverage this revenue-increasing potential. Social recommender systems are a reasonable technology for automated content aggregation. The technology is already being used in a new service type: Personalized News Aggregator (PNA). This is mostly optimized for use on mobile devices (e.g. tablet computers) and provides an individual selection of news and other content types within an optically appealing interface. Based on the technology of social recommender systems, news aggregators provide the requirements for establishing a new business model for news. If the system could automatically aggregate relevant content and articles for a user, this might lead to a higher willingness-to-pay for news.

These study results are a first indication of user adoption and the configuration of social recommender systems. Nevertheless, this study also contains some limitations. First, the sample consists mostly of students and might be not necessarily valid for the mass market. Therefore, if the technology evolves over time, this study should be repeated with a representative sample, in order to transfer the results to a wider population. Second, the research model only considered three key characteristics of social recommender systems. Although the inclusion of social information in a recommender system is suggested by our findings, it still remains unclear which particular information from a user's social network should be utilized to generate recommendations. Future research could thus explore additional external variables – that is, technical characteristics that were not included in this survey – to help draw a more complete picture of user acceptance for social recommender systems. Third, this study has explored the adoption of a social recommender system. While adoption is an important prerequisite, it is not the only factor that leads to a technology's success. The development of mobile internet and technologies might affect it in future. Therefore, in the case of an application system based on social recommender systems, it is important to understand the determinants of continuous use over time. Future research could explore the continuance and discontinuance of social recommender systems use.

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