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Abstract

The Internet provides large varieties of content, which renders consumption difficult for users. However, recommender systems filter and personalize content according to individual preferences and deliver solutions that take the problem of information overload into account. Previous studies show different approaches to classify existing recommender technologies. Nevertheless, these do not yet integrate social networking information. This study offers a systematic and up-to-date overview of three generations of recommender system technologies, including the latest development of social recommender systems. Also, the study delivers a typology and classification framework with the components of all types of recommender systems and their interactions. Separated between input, process (performed by technology and parameters) and output, we provide an overview to understand and visualize the recommendation process. Our results provide comprehensive insights in current recommender system technologies and are helpful for the design of business models and digitalization strategies.

Keywords: Recommender system, social network, classification

1 Introduction

Information personalization is as old as the Internet itself. In the past decade, much research has been done about personalization, in order to minimize the problem of information overload, referring to the high volume of information available but not consumable by the user. Hence, recommender system technologies have been used since the beginnings of e-commerce to suggest the right products to the right customers (Resnick & Varian, 1997). Nowadays, recommender systems do not only recommend physical products, but also digital products, such as news or music (H. Liu & Maes, 2005; Wei, Huang, & Fu, 2007). It is empirically shown that recommender systems have a positive effect on sales, as well as on the long-tail phenomenon in e-commerce (Pathak et al., 2010). The increasing interest in the personalization of web content and the use of automated technologies as recommender systems is also evident in the number of articles published in the past years, mainly in IS schools (Adomavicius & Tuzhilin, 2005b; Burke, 2002; Xiao & Benbasat, 2007). However, research on recommender systems also exists in branches of marketing, e-commerce, as well as economics and management science.

Due to the great success of social networks and the transformation of the Internet into so-called "social web," the use of social networking information (e.g. via the social network Facebook) in recommender systems is attracting the attention of various scholars (Arazy, Kumar, & Shapira, 2010; Guy et al., 2009; F. Liu & Lee, 2010; H. Liu & Maes, 2005). Whereas several articles contain classifications and taxonomies of recommender systems, the literature does not contain overviews that include this new technological approach (Adolphs & Winkelmann, 2010; Montaner, López, & de la Rosa, 2003; Xiao & Benbasat, 2007).

This points out a research gap in an overview that includes this latest technological development of combining classic recommender systems with social networking information. Therefore, the specific purposes of this study are: (1) to provide a literature based structured overview for recommender systems, (2) to develop a comprehensive and contemporary classification for current recommender system technologies, (3) to present a classification framework to understand the differences of these technologies in detail.

The paper is structured as follows: The next section gives a theoretical overview of recommender systems. Following, we identified three generations of recommender systems, classify and present them in detail. Based on these findings, we first present a typology to define and separate recommender systems from one another. Second, we develop a classification framework to understand the recommendation process in detail. The last section contains conclusions, implications, and limitations of the study.

2 Background

Recommender systems have been in existence since the introduction of the first system "Tapestry" of Goldberg et al. (1992) in the mid-1990s and provided a first solution to the customer's information overload problem. Recommender systems are Internet-based information systems, using a number of entities and selecting these based on users' preferences, profiles or behavior (Benlian, Titah, & Hess, 2010). As one of the first authors, Resnick and Varian (1997) stated that in a typical system "people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients". Burke (2002) further elaborated the definition as "describing any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options". Nowadays, recommender systems are broadly defined as "software tools and techniques providing suggestions for items to be of use to a user" (Ricci et al., 2011). Recommender systems can also be classified as a decision support system, enhancing the quality and efficiency for the user in decision situations, as well as offering a possibility to reduce the user's search costs (Xiao & Benbasat, 2007). Therefore, these technologies assist the user by supplying well-structured information in searching, sorting, classifying, filtering, and sharing the huge amount of information (Montaner et al., 2003). These arguments point out that the development of recommender systems stem from an e-commerce point of view. Famous examples are Amazon's product recommendation system, as well as Netflix's movie recommendation system.

There exist different classifications of recommender systems in the information systems literature. One of the first classification article presents an overview: Hanani, Shapira, and Shoval (2001) classify recommender systems in detail according to the operator's initiative, the operator's location, the filtering approach used, and the user's methods of acquiring knowledge. Due to the rapid technological development and using a different approach, Montaner et al. (2003) developed a classification of 37 different recommender systems on the Internet and classified them along 8 criteria, separated in profile generation dimensions (e.g. user profile representation) and profile exploitation dimensions (e.g. information filtering methods). Some years later, Manouselis and Costopoulou (2007) developed a classification of multi-criteria recommender systems. Wei et al. (2007) analyzed different recommendation approaches in detail, for instance the process of a recommendation approach in an e-commerce environment. Xiao and Benbasat (2007) developed a conceptual model from five theoretical perspectives for e-commerce product recommender agents. Adolphs and Winkelmann (2010) identified approximately 42 personalization articles in IS literature. The authors started to classify these articles using user-centric aspects (e.g., user experience, trust), method of implementation (e.g., algorithms, design), and according to theoretical foundation (e.g., methods, studies) (Adolphs & Winkelmann, 2010). Adomavicius, Manouselis, and Kwon (2011) improved their classification from classical personalization mechanisms to multi-criteria based personalization mechanisms.

3 Three Generations of Recommender Systems

The analysis is based on a literature review of journal articles and conference publications. As stated in Vom Brocke et al. (2009), rankings are an appropriate solution to ensure publication quality and to minimize the tremendous amount of literature. Therefore, we used rankings as a guide to find adequate information systems literature. We started to analyze exiting classifications, frameworks, categorizations, and state-of-the-art articles about personalization and recommender systems. We then clustered the specific knowledge about the processed information in the system and identified three generations.

3.1 Recommender System 1.0

Recommender system technologies that adjust content according to the users' individual preferences are simple and provide replicable behavior. These approaches in recommendation systems were restricted to reacting to direct or indirect user input, and follow a rule-based algorithm approach. In a simple form, the output of the recommendation is offered in a ranked list (Ricci et al., 2011). Input can be provided by explicit specifications, such as naming favorites (e.g., news topics such as sports) or implicit specifications (e.g., collecting usage data such as cookies and showing user browsing behavior) (Sundar & Marathe, 2010). Hence, several basic technological features are used to adapt information according to a user's implicit needs. Burke (2002) and Sundar and Marathe (2010) differentiate in detail between these two kinds of methods: personalization and customization. Personalization is defined as “tailoring product or service to a buyer’s preferences” (Burke, 2002). In this case, the system is the active part in the recommendation process – gathering implicit user operations, memorizing them, and recommending items similar to the viewed items. Similarity is estimated by considering the items’ properties, such as keywords. Due to the fact that the system adapts the content to a user’s needs on its own, these systems are defined as “system-tailored” personalization mechanisms. In contrast, customization is defined as “configuring a product or service to a buyer’s specifications” (Burke, 2002). In this case, the user is the active party, noting his or her interests and using the system to gather such explicit statements. The user can adjust the content and the system according to his or her interests, using the interface on his or her own. Due to this system-orientated customization process, these mechanisms are defined as “user-tailored” personalization mechanisms.

3.2 Recommender System 2.0

Classic recommender system technologies are extended algorithms that compare different keywords automatically, according to the user’s importance by weighting them. Most famous are content-based filtering, collaborative filtering, and hybrid filtering technologies (Adomavicius & Tuzhilin, 2005a).

A content-based filtering approach recommends items according to the correlation between an item’s content and the underlying user profile (Van Meteren & Van Someren, 2002). The decision to recommend an item to a user or not depends on how important item’s properties are to the user. The mere existence of a keyword is no longer sufficient for the selection of an item, since the weighting of the properties, assigned according to the user profile’s preferences takes priority. Thus, predictions are based on the relationships between the data and their importance (Balabanović & Shoham, 1997). The applicability of content-based filtering approaches is heavily dependent on a priori data about items and users. On the one hand, only properties of already known content are used as a basis for prediction-finding, defined as a cold-start problem. Hence, the algorithm can only find further items that are similar to already known items. Thus, other topics that could be of interest to the user are not covered at all. On the other hand, because the method is fundamentally based on the user’s past ratings, the algorithm initially knows too little about a new user to make accurate recommendations, defined as the over-specialization problem (Adomavicius & Tuzhilin, 2005b).

A collaborative filtering approach is defined as recommending items that “people with similar tastes and preferences liked in the past” to other users (Adomavicius & Tuzhilin, 2005b). Furthermore, there is a strong possibility that a user will like items that other people with same interests – defined as neighbors – have also liked in the past (Sarwar et al., 2001). Using this approach, collaborative filtering has the opportunity to solve the cold-start problem of content-based filtering by suggesting items rated by other users and not only by the current user. One solution is to use stereotypes in the basic user model to find good recommendations, even if there is only a limited amount of information about every user (Rich, 1979). Since this approach also considers other users’ preferences, the problem of over-specialization is solved. The involvement of other users with similar tastes improves recommendation results and presents suitable new topics to the current user (Balabanović & Shoham, 1997). Nevertheless, the collaborative filtering approach has certain limitations, such as the "new-item" problem, meaning that a collaborative system would not be able to recommend a new item before it was rated by a substantial number of users. Sparsity presents another problem. Because only a few people rate an item, it would rarely be recommended even if these users provided high ratings. For users with unusual preferences, the collaborative system would find few similar users, thus leading to poor recommendations (Adomavicius & Tuzhilin, 2005b). Hybrid recommender systems combine the two approaches, to achieve powerful synergies, as well as to gain better performance and to overcome individual disadvantages (Balabanović & Shoham, 1997; Burke, 2002).

3.3 Recommender System 3.0

Classic recommender approaches consider all user profiles as equal, but do not include the relationships between these profiles (Guy et al., 2009). Within the past years, during the rise of Web 2.0, social networks have spread, and social information as well as information about interpersonal connections have become public, for instance via the social network Facebook (Carmagnola, Vernero, & Grillo, 2009). Using this information, a new way to improve both the selection and the weighting of recommendations has become possible: social recommender systems (Arazy et al., 2010; Guy & Carmel, 2011).

When making a decision, a user can choose between different sources in order to internalize opinions that help him or her to take a decision. These sources can be divided into two categories, namely public opinions i.e. unfamiliar ratings, and personal opinions, i.e. ratings by friends or family members (He & Chu, 2010). Sinha and Swearingen (2001) propose that the best and most efficient source of information comes in the form of personal opinions which can be further classified in opinions from friends, acquaintances or friends of friends. These people present the highest power in influencing a user during his or her decision. Hence, for an efficient and reasonable recommendation, it is important to include personal as well as public opinion, with opinions stemming from preferences of friends. In comparison to classic recommender systems, the information of social relatives might have more influence in a distinctive situation than past activities from unknown people (Sinha & Swearingen, 2001). The main difference between the classic and social recommender approaches lies in the user's neighborhood, as well as in the quality of the neighborhood, which is examined by comparing different profiles. In classic recommender systems (like collaborative filtering), selection and weighing of the profile are carried out anonymously by the recommender system. As opposed to this, social recommender system technologies use information from the user's personal social network, and construct a user's neighborhood and furnish it with further detailed information. So, classic approaches define neighborhood profiles by considering similar behaviors in the past, whereas social approaches are based on the social distance between these profiles.

Arazy et al. (2010) state that social recommender systems use "data regarding users' social relationships in filtering relevant information to users, [...] for example, friendship ties in online social networks". Based on information about the users' social networking friends, such as the user's profile or information about the user's friends and in turn their profile, social recommender systems can recommend items. According to different scholars (Guy et al., 2009; Li & Karahanna, 2012), it might be possible to improve the accuracy of recommender systems by combining classic recommender systems with social network information: First, they begin collecting users' ratings and their social network relationships. Second, they collect neighbors' data and friends' data, in detail. Thirdly, the recommendations are calculated by combining the collaborative filtering results and the suggested neighbor groups. This approach improves recommender accuracy and reduces the duration of the calculation (F. Liu & Lee, 2010). H. Liu and Maes (2005) explains the necessity of social recommender systems as becoming "more central to people's lives, we must start modeling the person, rather than the user". As previously stated, the main theoretical basis for social recommender systems is that people generally prefer suggestions from their friends, due to a higher level of trust (Arazy et al., 2010; Sinha & Swearingen, 2001). Based on word of mouth theories, users benefit from social recommender systems by gaining access to recommendations from people they trust. In order to analyze the structures of social networks and to identify the relevance of different peers' preferences, social networking theories have to be applied. Much of social science research has focused on investigating the importance of friendships in social networks. First introduced by Granovetter (1973), social ties can be separated into strong ties and weak ties. Strong ties can be defined as people whom you really trust and who overlap with one's own social circles and provide similar characteristics. Instead, weak ties are only acquaintances, but provide access to new information. In the context of social recommender systems, the information of strength and distance of social ties can be used to generate recommendations, depending on whether the user desires more of the same items or redundant items (Seth & Zhang, 2008).

Social recommender systems analyze – in detail – the users' relationships to one another, and weight the recommendations according to the available information. The basis for this estimation can be derived from the underlying social network. By traversing the underlying network's graph, the social distance between users can be determined. In this neighborhood, the items' ratings are analyzed to find the highest-rated or most-recommended items, which in turn are used for recommendations for the current user. The smaller the distance between two peers in a network, the higher the algorithm weights an item (Van Meteren & Van Someren, 2002). People generally prefer suggestions from their friends, but also appreciate recommendations with unfamiliar content in order to broaden their horizons (Arazy et al., 2010; Sinha & Swearingen, 2001). Therefore, social recommender systems use the techniques of social distance and social proximity. Social distance, a concept from sociology, analyzes similarities between users regarding characteristics that define their identity such as their beliefs, customs, practices, or appearances. It estimates the extent of homogeneity between individuals according to a number of similar characteristics and it allows the technology to get information about the interpersonal relations between users (Akerlof, 1997). Social proximity seeks to connect people who are willing to collaborate with others within a network. It therefore analyzes the distance between two peers in the network as well as their familiarity and then compares their user profiles to estimate whether these peers are homogeneous enough to collaborate with each other (Zheng & Yano, 2007).

Carmagnola et al. (2009) propose a social network based algorithm that uses social information – for instance, social network data, comment, or tagging information, referring to the fact "that people are more likely to be interested in what people belonging to their social network like, independently of their real preferences". Besides familiar recommendations, Sinha and Swearingen (2001) also consider system transparency as a critical success factor for recommender systems. Using the social network data, social recommender systems can provide information about why content is recommended to a user, for instance, how many friends read the same article (Sinha & Swearingen, 2001).

4 A Classification of Recommender Systems

As seen in chapter 3, recommender systems can be separated in three generations. A classification presents all state-of-the-art information in one simple overview. We divided the classification in a typology (see chapter 4.1) and a classification framework (see chapter 4.2).

4.1 Typology

First, we define recommender system technologies and clearly separate them from one another in a typology (see table 1). We can classify these generations by four different criteria. First, quality criterion describes the processing of information in the recommender system. Second, parameter explains necessary input for the technology in the recommendation generation process. Third, technology shows the underlying algorithm and processing technique. The fourth parameter, progress, describes the adaptiveness of the recommender system, based on user's actions in the recommendation process.

Type	Quality criterion	Parameter	Technology	Progress
Recommender system 1.0	Information processing	Explicit / Implicit preferences	Rule-based	Static
Recommender system 2.0	Behavior processing	Explicit / Implicit preferences	Content-based Collaborative Hybrid	Dynamic (Recursive)
Recommender system 3.0	Social networking information	Explicit / Implicit preferences Social networking information	Hybrid	Dynamic (Recursive)

Table 1: Typology of recommender systems

4.2 Classification Framework

In this section, we develop a classification framework to provide an extended overview in order to better understand and to visualize the recommendation process (see figure 1). According to Xiao and Benbasat (2007) we divide the process into input, process (performed by technology and parameters) and output. Illustrating the linkage and dependency between these individual processing steps are important for understanding the recommendation process behavior and improving its performance.

We determine two different input variables for the initial phase of a recommendation process, namely content and initial user profile. Different content types can be recommended to the user, e.g. text, video content, or music. Furthermore, the system needs an initial user profile that provides basic information about the user to filter content. The initial profile also has different states. It can be empty, filled manually by the user or the system, or initialized by training sets or stereotyping.

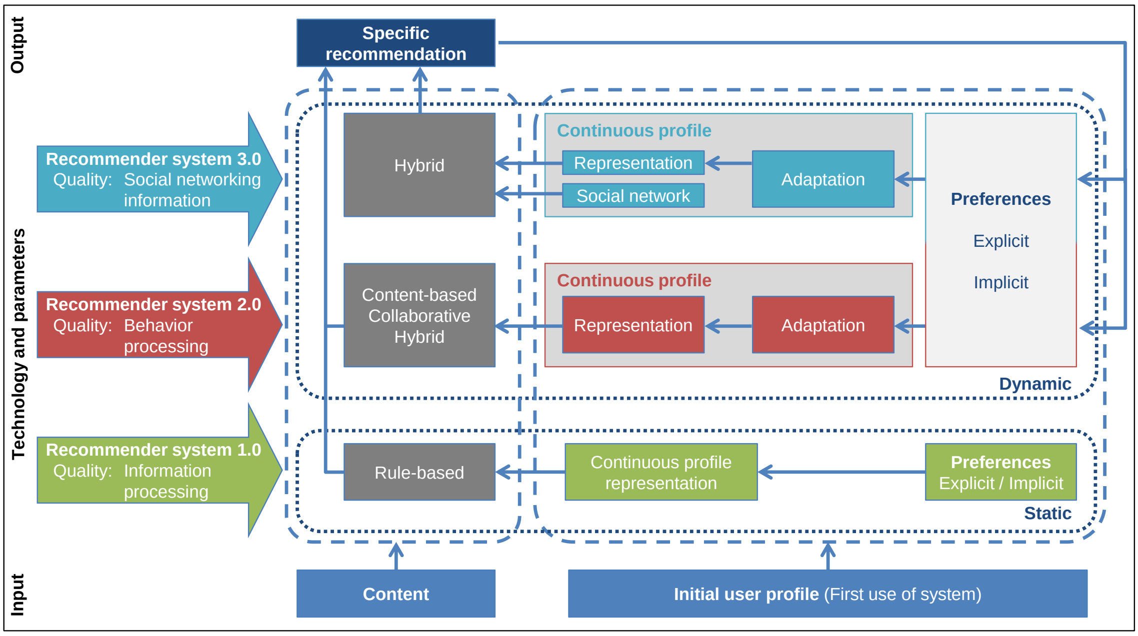

Figure 1: Classification framework of recommender systems

The classification's processing part describes the use of technologies and associated parameters. We distinguish between static and dynamic mechanisms: Static mechanisms provide unidirectional interaction with the user. Dynamic mechanisms provide bidirectional interaction with the user, adapting previous inputs and resulting in a recursive behavior. Furthermore, considering parameters in detail, explicit and implicit user preferences as well as ratings continuously adjust the user profile during the recommendation process. Explicit user ratings, in which the user is asked to indicate personal characteristics or rate items due to personal preferences, are the most precise ratings (Jannach et al., 2010). Explicit ratings' primary disadvantage is that the system requires additional effort, especially decision effort, from the user (Xiao & Benbasat, 2007). Instead, implicit ratings are automatically collected from the recommender system, for example, implemented in an online shop when a customer buys a product it will be interpreted as a positive rating (Jannach et al., 2010). An important problem with this approach is that the user behavior could easily be misinterpreted.

After the initial use of the system, the initial profile becomes a continuous user profile. The profile is updated by explicit or implicit preferences and provides the essential data for the technology’s algorithm. Thus, to work well, the system needs as much user data as possible. The user profile can also be enriched with information by using inductive learning techniques, clustering, or simple positive reinforcement techniques. Furthermore, manual updating techniques, adding new information, gradual forgetting, or natural selection of relevant information are used (Montaner et al., 2003). The profile itself can subsequently be represented in different ways to provide consistent data for the algorithms. It can either provide only basic user information in recommender systems 1.0, or these can be updated by explicit or implicit ratings of the user, such as in recommender systems 2.0. They can even be improved by the social networking information of a user in recommender systems 3.0. The starting point in a social recommender system is the information about its users’ relationships and their social distance, obtained from a social network, e.g. Facebook. In a simple version, the numbers of hops of the shortest paths between friends or even friends of friends are displayed in a distance matrix. This information is stored in the continuous user profile and serves as input data for the generation of a recommendation. Examples are information about the users, items they interacted with and information about the relationship between them. As with a classic recommender system, the social recommender system then generates recommendations based on this input data. Instead of similar information based on previous ratings, social recommendations are based on items that were used or were rated highest by those peers, to whom the user is closest or trusts the most (Arazy et al., 2010). Most often, the social recommender system uses external data sources to collect the required input data, e.g. Facebook or Twitter. Nevertheless, other examples as FilmTrust use an own, internal social network to generate the required social information. Typical profile representation techniques include feature vector types, user-item rating matrix or weighted semantic networks (Montaner et al., 2003). Regarding technologies, we define rule-based algorithms to filter the content by user information and pre-defined keywords, being processed by simple rules. As noted, this static mechanism is not influenced by user ratings about the recommendation. Furthermore, we include content-based filtering, collaborative filtering, and hybrid algorithms. These technologies are the most common in recommender systems.

Finally, the output of the recommender system is a highly specific recommendation of content, depending on different user input determinates. After the consumption of content by a user, he or she can rate the content only via dynamic mechanism systems. This rating – explicit or implicit – as well as updates in the social network will automatically and recursively influence the continuous user profile in the recommender system, and will be used in the next recommendation process to improve the presented results.

5 Conclusion, Implications, and Limitations

The primary objective of this investigation was to classify existing recommender systems, because no current classification framework has integrated new technology through the use of social networking information. For this classification, first a typology has been developed in order to systematize the high amount of three generations of recommender systems. Second, a classification framework illustrated the recommendation process, its linkage and dependencies. The results show that this new technology has changed the presence of classic recommender systems and has further improved the recommendation process that benefits through the addition of social networking information, which might lead to higher recommender accuracy.

On the one hand, as theoretical implication, we contribute to existing research about recommender systems research. As a result, we improve existing theoretical models by the latest technological development in social networks. In this way, we have extended state-of-the-art science by means of an updated classification framework and have proposed an enhanced set of criteria to analyze recommender systems in future. There are also practical implications. Technology, e-commerce, or media companies can use our classification to improve, review, or adjust their current implementations. Besides, companies can also benefit in order to develop new digital approaches that combine classic recommender systems and social networking information right from the start of the development. Some organizations already apply this new technology in an e-commerce context. Amazon's "Tap into your friends," combines data from Facebook with its existing recommender system. The user receives recommendations based on his or her friends' Facebook likes and favorites. This example supports our findings that recommendations by friends might have more value than unknown recommendations.

Our investigation also has some limitations. First, our conclusions are derived solely from an extensive and detailed literature review; it provides an abstract overview. No empirical data was compiled. However, a range of previous studies on this subject and their classifications are based on state-of-the-art literature reviews and supports our research. The second limitation concerns the rapid development of new technologies in this research area. We provided a overview, addressing all current technical issues and evolutions. Thus, the classification could be adjusted so as to integrate further technological development in the near future.

References

Adolphs, C., & Winkelmann, A. (2010). Personalization Research in E-Commerce - A State of the Art Review (2000-2008). Journal of Electronic Commerce Research, 11(4), pp. 326-341.

Adomavicius, G., Manouselis, N., & Kwon, Y. (2011). Multi-Criteria Recommender Systems Recommender Systems Handbook. In F. Ricci, L. Rokach, B. Shapira & P. B. Kantor (Eds.), Recommender Systems Handbook (pp. 769-803). New York: Springer.

Adomavicius, G., & Tuzhilin, A. (2005a). Personalization technologies: a process-oriented perspective. Communications of the ACM, 48(10), pp. 83-90.

Adomavicius, G., & Tuzhilin, A. (2005b). Towards the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge and Data Engineering, 17(6), pp. 734-749.

Akerlof, G.A. (1997). Social distance and social decisions. Econometrica: Journal of the Econometric Society, pp. 1005-1027.

Arazy, O., Kumar, N., & Shapira, B. (2010). A theory driven design framework for social recommender systems. Journal of the Association for Information Systems, 11(9), pp. 455-490.

Balabanović, M., & Shoham, Y. (1997). Fab: content-based, collaborative recommendation. Communications of the ACM, 40(3), pp. 66-72.

Benlian, A., Titah, R., & Hess, T. (2010). Provider- vs. User-generated Recommendations on E-Commerce Websites – Comparing Cognitive, Affective and Relational Effects. In: Proceedings of the International Conference on Information Systems, December 12-15. St. Louis, USA: ACM Press.

Burke, R. (2002). Hybrid recommender systems: Survey and experiments. User Modeling and User-Adapted Interaction, 12(4), pp. 331-370.

Carmagnola, F., Vernero, F., & Grillo, P. (2009). Sonars: A social networks-based algorithm for social recommender systems. In: Proceedings of the 17th International Conference on User Modeling, Adaptation, and Personalization, June 22-26 (pp. 223-234). Trento, Italy: Springer-Verlag.

Goldberg, D., Nichols, D., Oki, B.M., & Terry, D. (1992). Using collaborative filtering to weave an information tapestry. Communications of the ACM, 35(12), pp. 61-70.

Granovetter, M.S. (1973). The Strength of Weak Ties. American journal of sociology, 78(6), pp. 1360-1380.

Guy, I., & Carmel, D. (2011). Social recommender systems. In: Proceedings of the 20th international conference companion on world wide web, March 28 - April 01 (pp. 283-284). Hyderabad, India: ACM Press.

Guy, I., Zwerdling, N., Carmel, D., Ronen, I., Uziel, E., Yogev, S., & Ofek-Koifman, S. (2009). Personalized recommendation of social software items based on social relations. In: Proceedings of the 3rd ACM conference on recommender systems, October 22-25 (pp. 53-60). New York, USA: ACM Press.

Hanani, U., Shapira, B., & Shoval, P. (2001). Information Filtering: Overview of Issues, Research and Systems. User Modeling and User-Adapted Interaction, 11(3), pp. 203-259.

He, J., & Chu, W.W. (2010). A social network-based recommender system (SNRS). Data Mining for Social Network Data, 12, pp. 47-74.

Jannach, D., Zanker, M., Felfernig, A., & Friedrich, G. (2010). Recommender Systems: An Introduction. New York: Cambridge University Press.

Li, S., & Karahanna, E. (2012). Peer-Based Recommendations in Online B2C E-Commerce: Comparing Collaborative Personalization and Social Network-Based Personalization. In: Proceedings of the 45th Hawaii International Conference on System Sciences, January 4-7 (pp. 733-742). Maui, USA: IEEE.

Liu, F., & Lee, H.J. (2010). Use of social network information to enhance collaborative filtering performance. Expert Systems with Applications, 37(7), pp. 4772-4778.

Liu, H., & Maes, P. (2005). Interestmap: Harvesting social network profiles for recommendations. In: Proceedings of the Beyond Personalization 2005 Workshop, January 9-12. San Diego, USA.

Manouselis, N., & Costopoulou, C. (2007). Analysis and Classification of Multi-Criteria Recommender Systems. World Wide Web, 10(4), pp. 415-441.

Montaner, M., López, B., & de la Rosa, J. (2003). A Taxonomy of Recommender Agents on the Internet. Artificial Intelligence Review, 19(4), pp. 285-330.

Pathak, B., Garfinkel, R., Gopal, R., Venkatesan, R., & Yin, F. (2010). Empirical analysis of the impact of recommender systems on sales. Journal of Management Information Systems, 27(2), pp. 159-188.

Resnick, P., & Varian, H. (1997). Recommender systems. Communications of the ACM, 40(3), pp. 56-58.

Ricci, F., Rokach, L., Shapira, B., & Kantor, P. (2011). Introduction to Recommender Systems Handbook. In F. Ricci, L. Rokach, B. Shapira & P. B. Kantor (Eds.), Recommender Systems Handbook (pp. 1-35). New York: Springer.

Rich, E. (1979). User modeling via stereotypes. Cognitive science, 3(4), pp. 329-354.

Sarwar, B., Karypis, G., Konstan, J., & Reidl, J. (2001). Item-based collaborative filtering recommendation algorithms. In: Proceedings of the 10th International Conference on World Wide Web, May 1-5 (pp. 285-295). Hong Kong, China: ACM Press.

Seth, A., & Zhang, J. (2008). A social network based approach to personalized recommendation of participatory media content. In: Proceedings of the 2nd International Conference on Weblogs and Social Media, March 30 - April 2. Seattle, USA: AAAI Press.

Sinha, R., & Swearingen, K. (2001). Comparing recommendations made by online systems and friends. In: Proceedings of the 2nd DELOS Network of Excellence Workshop on Personalization and Recommender Systems in Digital Libraries, June 18-20 (pp. 1-6). Dublin, Ireland.

Sundar, S., & Marathe, S. (2010). Personalization versus Customization: The Importance of Agency, Privacy, and Power Usage. Human Communication Research, 36(3), pp. 298-322.

Van Meteren, R., & Van Someren, M. (2002). Using content-based filtering for recommendation. In: Proceedings of ECML 2000 Workshop: Machine Learning in New Information Age, May. Barcelona, Spain.

Vom Brocke, J., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R., & Cleven, A. (2009). Reconstructing the giant: on the importance of rigour in documenting the literature search process. In: Proceedings of 17th European Conference On Information Systems, June 8-10 (pp. 2206-2217). Verona, Italy.

Wei, K., Huang, J., & Fu, S. (2007). A survey of e-commerce recommender systems. In: Proceedings of the International Conference on Service Systems and Service and Service Management, June 9-11 (pp. 1-5). Chengdu, China: IEEE.

Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. MIS Quarterly, 31(1), pp. 137-209.

Zheng, Y., & Yano, Y. (2007). A framework of context-awareness support for peer recommendation in the e-learning context. British Journal of Educational Technology, 38(2), pp. 197-210.