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# Applying recommender systems in collaboration environments

Ernesto Damiani [a], Paolo Ceravolo [b,*], Fulvio Frati [b], Valerio Bellandi [b], Ronald Maier [c], Isabella Seeber [c], Gabriela Waldhart [c]

[a] *Etisalat British Telecom Innovation Center/Khalifa University, Abu Dhabi, United Arab Emirates*
[b] *Computer Science Department, Università degli Studi di Milano, Italy*
[c] *Department of Information Systems, Production and Logistics Management, University of Innsbruck, Austria*

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ABSTRACT

Team-based organizational structures are now widely adopted for activities such as product development, customer support and process-improvement initiatives due to their increased likelihood of making better decisions and solving problems. However, team collaboration often faces pitfalls like information overload or misunderstandings due to goal misalignment. In this paper, we put forward the idea that computer-supported collaboration environments can have a positive impact on team collaboration by increasing team members' awareness, focusing attention on task execution, and fostering the frequency of interaction among team members. We study the impact of recommender systems on team processes in computer-supported collaboration environments, describing the results of two experiments that show how recommendations impact interactions in teams. Teams using recommendations spent less effort on information handling and engaged more in communication than teams without recommendations.



## 1. Introduction

Organizations are characterized by an increasing share of knowledge work (Wolff, 2005) and the corresponding transformation of organizational structures from work organized around individuals to team-based work structures. One central cornerstone of teams is that any decision, solution, or new idea represents a product that has emerged from the teams interactions and is not attributable to an individual alone (Keyton, Beck, & Asbury, 2010). The team members' fruitful collaboration represents the basis for driving innovation and organizational success (Mathieu, Maynard, Rapp, & Gilson, 2008). Many teams face obstacles in their collaboration, such as problems when and how to communicate, leading to poor communication; they might be unaware of the other team members' knowledge hindering the synthesis of diverse knowledge that could be brought to solve problems or perform the task at hand (Huckman & Staats, 2013). They might experience information overload, which could lead to the breakdown of communication and higher time requirements for information handling (Eppler & Mengis, 2004).

Past research underlined the positive impact of computer-supported collaboration in that it can increase team members' awareness (Dourish, 1997; Seeber et al., 2013), orient their attention towards task execution (Siampou, Komis, & Tselios, 2014) and increase their frequency of interaction (Tutty & Klein, 2008). When teams find ways to improve their communication, they can reduce time-consuming coordination activities (Malone & Crowston, 1990) in favor of task-related information exchange and work on the tasks for improved team performance (Kozlowski & Ilgen, 2006). According to Feedback Intervention Theory, automated feedback has a guidance effect on the team members attention (Kluger & DeNisi, 1996). Feedback not only affects the behavior of individuals, but also impacts the behavior of teams and consequently team performance (Wheeler & Valacich, 1996). General purpose recommender systems (Ricci, Rokach, & Shapira, 2011) are increasingly appreciated in collaborative settings as they aim to support information processing among team members (Limayem & DeSanctis, 2000) and decrease information overload by suggesting items likely to be relevant (Terveen & McDonald, 2005). So far, research on team-based interventional feedback (Chenoweth, Dowling, & Louis, 2004; Limayem & DeSanctis, 2000; Todd & Benbasat, 1992; Wong & Aiken, 2003) has mostly investigated the impact on team outcomes (Seeber, Maier, & Weber, 2014), but hardly considered the so often theorized effect on team processes (Mathieu et al., 2008).

In this paper, we focus on the impact of recommender systems (Ricci, Rokach, & Shapira, 2011) on team processes in computer-supported collaboration environments, e.g., Limayem and DeSanctis (2000), Wong and Aiken (2003), and Mathieu et al.

* Corresponding author.

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(2008). We aim at extending the current understanding of the effects of recommendations in such collaboration environments by investigating how recommendations impact interactions in teams. For this purpose, we conducted two laboratory experiments. The first experiment studied the difference of communication and coordination between a treatment group of teams receiving recommendations and a control group of teams receiving no recommendations when working on a decision-making task. The second experiment explored changes in interactions of teams receiving recommendations. The implemented Recommender System is part of the Innovation Factory (IF), a computer-supported collaboration environment. The RS, visualized as a tag cloud, recommends knowledge elements to users based on the topic which they are currently writing about (Bellandi et al., 2012).

The paper is organized as follows: Section 2 discusses related work and Section 3 describes the Innovation Factory as the collaboration environment adopted in our experiments. Section 4 describes the study design and Section 5 discusses the results of our laboratory experiments before Section 6 presents our conclusions.

## 2. Related work

### 2.1. Recommender systems

The term Recommender System (RS), was introduced for the first time in 1997 by Resnick and Varian (1997). A RS aims at rating resources according to the interest a specific user will show in them within a dedicated resource space. Typically, this prediction is made by considering implicit or explicit ratings expressed by other users on the same resources (Adomavicius & Tuzhilin, 2005). As studies on RS are relatively recent and interest in their applications is growing, the state of the art is rapidly evolving. At the present time we can distinguish between five main approaches for implementing recommender systems.

- *Content-based:* the RS rates resources based on their degree of similarity with other resources already rated by the same user.
- *Collaborative-filtering:* the RS rates resources for a user based on implicit or explicit ratings provided by other users. The final rate of a resource depends on the similarity between the users who rated the resource and the user querying the RS. It should be noted that collaborative-filtering is today the most popular technique for implementing RS.
- *Demographics-based:* the RS rates resources based on similarity between demographics (age, gender, country of residence) of users who rated the resource high and those of the user querying the RS. The benefit of a demographics-based approach is that it does not require a complete history of user ratings of the type needed by collaborative techniques.
- *Social Network-based:* the RS rates resources based on preferences expressed by users sharing a social relation with the user querying the RS. This approach is typically used in combination with collaborative filtering techniques.
- *Hybrid RS:* the system rates the items to be suggested based on a combination of the approaches described above. Robin Burke has written a complete classification of hybrid systems (Burke, 2002), listing a number of hybridization methods to combine pairs of recommender algorithms.

All the above mentioned techniques have a common drawback: the "cold-start" problem also known as the "early rater" or "sparse ratings" problem (Sarwar et al., 1998). The RS requires a critical mass of ratings available in order to compute good quality ratings. While ratings are initialized manually in many systems, the need to address the"cold-start" problem has fostered research on *knowledge-based* RS that rate resources based on resource descriptions (De Gemmis et al., 2010). Using an inference engine, the RS computes the best match between a resource description specified by the user and description on resources available in its knowledge base.

Other studies (Fleder & Hosanagar, 2009) discuss the advantages and disadvantages of the different RS algorithms, comparing collaborative-filtering to content-based or knowledge-based. The main advantages of collaborative-filtering are related to its simplicity: it is domain independent and can work with a relatively simple data structure. The main disadvantage is that collaborative-filtering techniques cannot recommend resources when historical data are insufficiently available.[1] Content-based or knowledge-based techniques do not suffer from the "cold-start" problem and can work even with a limited data set; however, the process of content encoding and representation is not trivial, as it is highly domain-dependent and very expensive if it cannot be automated from independent organizational processes (Drachsler, Hummel, & Koper, 2008).

Empirical studies have shown that there is no "absolute best" among collaborative-filtering, content-based and knowledge-based techniques. In Tacchini (2012) the listening data of approximately 360,000 unique users of the social radio *Last.fm*[2] were analyzed to compare the quality of the similarity scores obtained by classical collaborative-filtering based on user preferences and by a knowledge-based technique based on folksonomy. In Bogers and van den Bosch (2009) the authors performed experiments on three datasets, namely Delicious,[3] CiteULike[4] and BibSonomy[5] and compared a range of collaborative and content-based techniques with respect to item recommendation. The results showed that the combination of collaborative and content-based techniques obtained the best performance.

### 2.2. Recommender systems in technology enhanced learning

Recommender systems have attracted much interest in the Technology Enhanced Learning (TEL) domain due to their high potential of eliciting relevant learning resources (Wang & Hannafin, 2005). Since information retrieval, in terms of searching for relevant learning resources, is a pivotal activity in TEL, RS for TEL applications (RS-TEL) have attracted much interest. Probably the most complete survey on RS-TEL is Manouselis, Drachsler, Vuorikari, Hummel, and Koper (2011). In the conclusions, the authors discuss the validation problem of RS-TEL, highlighting the fact that a systematic comparative evaluation of RS-TEL systems is still lacking.

Nevertheless, some interesting experimental results are available, even if the different studies do not allow for a systematic comparison, due the heterogeneity of the experimental designs that were adopted. The work (Ogata & Yano, 2000) emphasizes the positive effect that RS have on calling the attention of users to other users accessing the same resources, e.g. via a message like "someone is looking at the same knowledge that you are looking at". By letting a user know that other users also access or have accessed the same resource, a certain level of justification of the item's relevance is given. This, in turn, positively affects the trust that users have in the RS suggestions. Moreover, several studies discuss the role that justification and explanation of recommendations have when improving the quality of the user interaction with

[1] The above mentioned "cold-start" problem.
[2] http://www.last.fm.
[3] http://delicious.com.
[4] http://www.citeulike.org.
[5] http://www.bibsonomy.org.