Association for Information Systems
AIS Electronic Library (AISeL)

ICIS 2006 Proceedings

International Conference on Information Systems (ICIS)

December 2006

'Friends Group' in Recommender Systems: Effects of User Involvement in the Formation of Recommending Groups

Dan-Gur Yuval
University of Haifa

Rafaeli Sheizaf
University of Haifa

'Friends Group' in Recommender Systems: Effects of User Involvement in the Formation of Recommending Groups

Social, Behavioral and Organizational Aspects of Information Systems

Yuval Dan-Gur
InfoSoc, University of Haifa
yuvald@gsb.haifa.ac.il

Sheizaf Rafaeli
InfoSoc, University of Haifa
sheizaf@rafaeli.net

Abstract

How can we improve the acceptance of recommendations in collaborative systems? The group identity of recommenders and recipient involvement in group formation impacts on the likelihood that users of social collaborative systems would accept recommendations provided on it. We introduce the term 'friends group' to describe a sub-group of the 'neighbors group' in recommender systems that is not solely rank-dependent, as opposed to 'neighbors' that are assigned by rating similarity. The 'friends group' is unique because of the user's involvement in its formation and the user's ability to choose the characteristics of its members. The latter aspect corresponds to Festinger's "Social Comparison Theory", suggesting that 'neighbors' (like-minded groups) are relevant for 'low-risk' domains whereas similarity-based 'friends' are more relevant for 'high-risk' domains.

We conducted a two year field study, using QSIA, a Web-based Java-programmed collaborative system for collection, management, sharing and assignment of learning knowledge items. QSIA was implemented in over ten courses in several universities. QSIA database and logs contained approximately 31,000 records of items-seeking acts, 3,000 users, 10,000 items, 3,000 rankings and knowledge items from 30 domains.

We found that the difference between acceptance and rejection ratios of recommendations when the items originated from an advising group comprised of 'friends', is significantly higher than when the advising group is the more commonly known 'neighbors group'. The difference increases for frequently recommended as opposed to other items and for experienced as opposed to 'average' users. Our longitudinal analysis indicates a positive learning curve for experienced users, who, over time, increasingly preferred 'friends group' over 'neighbors group' as their experience with the system increases. Also, users chose their own group to participate in the advising group significantly more than other groups.

The contribution of this study is in explicating the relationship between the perceived quality of the recommendation (measured in terms of "usage actions"), and the user's involvement in the formation of the advising group. The major implication of our findings for the development of recommender systems is the need to enhance involvement of recommendation seekers in the process of forming the advising group. Developers of recommender systems should consider increasing users' control over relevant characteristics of the members of this group.

Keywords: Recommender systems, collaborative filtering, friends group, QSIA, knowledge items.

Introduction

Computerized information tools to locate information are outpaced by the growth of information (Belkin, 2000; Cosley et al., 2003; Oard and Kim, 1998). There are various solutions, some still in their experimental phases, that were developed to bridge this gap. Most efforts can be categorized into one of the following:

- Enriching the database (e.g. tagging, keywords or indexing) to support efficient searches.
- Improved algorithms for quality and precision.
- Improved understanding of user's needs and profiles

Despite progress made in these directions, these approaches have in common a focus on an isolated individual interacting with a machine using mathematical methods or information retrieval.

In contrast, *Recommender Systems*, aimed at locating *subjectively* relevant information out of large data volumes, have several unique characteristics:

- They introduce the *collaborative aspect* of filtering to the search, contributing to better results. The opinions of others in the search space become a central issue, replacing previous foundations such as the wisdom and excellence of algorithm developers (Rafaeli et al., 2005).
- User models are simplified and more task-oriented: instead of the requiring exact queries, users are only asked to rate and evaluate items to the degree that they are relevant and worth consuming.
- The requirements from the item domain are narrowed down to just being *ratable*. No machine-parsed items are necessary as in Information Retrieval (IR) (Shardanand and Maes, 1995; Traill et al., 1997). This simplicity opens the domain to "taste products", whose relevance is completely subjective and almost cannot be evaluated by experts for distinct users.

Our main research questions stem from the assertion that even in an automated system, recommendation giving and taking are social processes and these corresponding aspects must be assigned proper weights. Accordingly, we hypothesized that users will prefer to assume more control over the recommendation process, especially over the formation of the recommending group. This preference will be reflected in a higher level of acceptance of recommended items when the recommendations originate from 'friends groups', which are controlled by the user. We also assumed that given the opportunity, users would choose similar-to-themselves 'friends' for their advising group in accordance with the "Social Comparison Theory" (Festinger, 1954).

Recommender Systems

The core task of a recommender system is to recommend, in a personalized manner, interesting and valuable items and help users make appropriate choices from a large number of alternatives, without sufficient personal experience or awareness of the items' alternatives (Grasso et al., 2000; Oard and Kim, 1998; Resnick and Varian, 1997).

The domain of recommender systems has expanded during the last decade with commercial applications (Soboroff et al., 1999) and has become an integral part of E-Commerce sites like Amazon.com, CDNow (Schafer et al., 1999) and eBay (Resnick et al., 2000).

Item Domains

Items of recommender system can be "taste products" (Freedman, 1998; Pescovitz, 2000), like lifestyle (Ujjin and Bentley, 2001), ski resorts (SkiMatcher recommender system), supermarket products (Lawrence et al., 2001), movies, music albums (Herlocker et al., 2000; Shardanand and Maes, 1995), books (Book Forager recommender system; Freedman, 1998), and even jokes (Goldberg et al., 2001).

On the other hand, items can be "knowledge products", scientific (Geyer-Schulz et al., 2000), research oriented (Delgado et al., 1998), organizational learning (Linton et al., 2000), or Usenet messages and Web resources (Bollacker et al., 1999; Goldberg et al., 1992; Konstan et al., 1997; Terveen et al., 1997).

Algorithms

Research suggests that people can become good recommendation providers and have their opinions and preferences included in the recommendation process of other users based on *preference similarity* where the recommendation provider's opinions have high similarity with those of the recommender seeker (Herlocker et al., 2000; Resnick and Varian, 1997; Shardanand and Maes, 1995). Recommender systems approach the problem of helping users find preferred items mainly with the technique of Collaborative Filtering (CF). The basic idea of CF algorithms is to predict the top-N recommended items based on the opinions of like-minded users (Sarwar et al., 2001); the task is to predict the utility of items to a particular user (the 'active' user) based on a dataset of users' votes from a sample population of the other users. These systems employ statistical techniques to find a group of users known as *'neighbors'* that have a history of agreeing with the active user (because they rated common items similarly) and then different algorithms are used to combine preferences of neighbors to produce a prediction of top-N recommendations for the active user (Karypis, 2000; Sarwar et al., 2001). The techniques are also known as *nearest-neighbor* or *user-based* CF.

Weaknesses and Limitations

Recommending items to users based on the weighted ratings of the top-N neighbors seemed to work. Soon though, problems and limitations emerged based on practical experiences (Grasso et al., 2000; Lawrence et al., 2001; Resnick and Varian, 1997; Terveen and Hill, 2001; Ujjin and Bentley, 2001). The main reported problems:

- *Black boxes* provide no transparency into the working of the recommendation procedure (Herlocker et al., 2000).
- *Exploration/Exploitation tradeoff* – whether to recommend a wide range of untested items or a narrow range that match the known user profile (Balabanovic, 1998).
- *Initial user profile* - the system's 'perception' of a new user, is difficult to form and formulate though it has great importance for future recommendations (Maltz and Ehrlich, 1995).
- *Data sparseness and 'first rater' problem* – the number of people who have rated the items is relatively small compared to the number of items (Terveen and Hill, 2001) and users do not often 'volunteer' to rate a new item.
- *Performance speed* – systems with a large volume of data (items x users) are slowing down if online computing is executed whenever recommendations are needed (Sarwar et al., 2001).

Is Social Collaboration Really 'Social'? – HCI and Social Aspects

We suggest that *recommendation seeking is a natural social process* that exists since the early days of tribal humanity (Cosley et al., 2003; Jungermann, 1999), and should be examined accordingly even when the process is automated.

Many studies (Moon and Nass, 1998; Nass and Moon, 2000; Wood and Taylor, 1991) have demonstrated that even the human-computer dyad presents social rules and follows some well-established behavioral patterns as people attribute human qualities to computers.

Our literature review of recommender systems did not provide evidence that Automated Collaborative Filtering (ACF) is really "social": only little notice has been paid to the social aspects of recommender systems and to the unsuitability they impose on the natural process of seeking and providing recommendations. The following are some typical social aspects that do not have an equivalent in recommender systems:

- People have the ability to choose their recommendation providers.
- Querying and asking for explanations for the recommendation is impossible in most systems, yet it is still considered an important feature (Herlocker et al., 2000; Preece, 1999; Terveen and Hill, 2001).
- In 'real life', one can filter recommendation producers based on the item under concern or the situated environment.

Attributing Human Qualities to Computers

How do people respond to advice from a machine? Do they attribute social rules to the computer (Nass and Moon, 2000)? Do they treat it as a 'computerized oracle' (Herlocker et al., 2000)? Consequently, is the real challenge to deliver recommendations to the user in a 'natural manner' (Gates et al., 1999) or merely to automate the process (Lueg and Landolt, 1998)?

We recall that Alan Turing's test for an intelligent machine is that it must "seem" intelligent (Turing, 1950). Nass and Moon (2000) review a series of experimental studies showing that individuals apply social rules and expectations to computers. These studies indicate that people apply gender stereotypes and behaviors – such as politeness and cognitive commitment.

Moon (1998) suggests, in accordance with previous research, that computers are readily recognized by users as being "similar" or "dissimilar" to themselves based on minimal, text-based manipulations of the 'computer's personality'. This perceived similarity has major effects on human-computer relationships: users are more "socially attracted" to similar computers (compared with dissimilar ones) and find the former to be more "intelligent" and more enjoyable to interact with. Though it may seem difficult to conceptualize similarity with respect to human-computer interaction (Moon and Nass, 1998), interfaces that take into account the "computer character" have been introduced (Ujjin and Bentley, 2001).

Accepting Advice from a System

How is advice from a machine accepted by users? Do people tend to follow it more than suggestions from other people (Swearingen and Sinha, 2001)? Does it follow the same pattern of "social" footprints that Nass and Moon drew while attributing to machines human qualities (Moon and Nass, 1998; Nass and Moon, 2000)? Is this form of computer-mediated communication outperformed by the traditional "face to face" process?

Research shows that expert system advice is not always evaluated in terms of its contents; rather, users are persuaded because they have certain beliefs about advice given by a computer. Following the same argumentation, systems are thought to be more objective and rational than human advisors (Dijkstra et al., 1998). Evaluation of computerized advice is frequently reported to be biased and users are not always aware of the system's inaccuracies (Dijkstra, 1998, 1999), as computerized systems make information look more credible (Dijkstra, 1998, 1999; Dijkstra et al., 1998; Murphy and Yetmar, 1996). It should be noted though, that there are a few studies that contradict to some extent the higher level of confidence in the system compared with human experts (Fogg and Tseng, 1999; Lerch and Prietula, 1989; Swearingen and Sinha, 2001). Computers gain credibility when they provide accurate information to users find and lose credibility when providing erroneous information. Minor computer errors have disproportionately large effects on perceptions of credibility (Fogg and Tseng, 1999). Familiarity and trust were found to be a dominant issue even in the (so called) "limited context" of a user that buys books from Amazon.com and not constrained only to two-way extensive direct interactions between people (Gefen, 2000).

The Concept of 'Friends Group'

We chose to concentrate on the social aspects of user involvement in the recommendation process, specifically in the formation of the advising groups.

A 'neighbors group' consists of those users who are statistically similar to the recipient. We introduced the term *'friends group'* to describe a sub-group of neighbors that are purposefully selected by the user. In the case of our research tool, QSIA system, the user can choose the groups/classes that can populate the 'friends group', the role (teacher or student) of its members, and the relative grade level of the participants of his/her 'friends group'.

The differences between the 'friends group' and the frequently used 'neighbors group' are substantial in at least two aspects:

- The *user is involved* in forming the recommending group rather than relying upon an automatic, completely machine-generated procedure.
- The *user can choose the characteristics* required for a recommendation provider to be included in the 'friends group'.

Our concepts emerged mainly from the "Social Comparison Theory" but also from other findings that presented limitations of recommender systems. For example:

- Users' opinions are affected by the ratings that systems present (Cosley et al., 2003).
- People demand transparency of recommendation processes and do not like "magical" outputs (Herlocker et al., 2000; Preece, 1999; Terveen and Hill, 2001).
- Human taste is not stable (Freedman, 1998; Pescovitz, 2000).

Social Comparison Theory

Recommender systems apply closest-neighbor algorithms to find like-minded users (Breese et al., 1998; Karypis, 2000; Sarwar et al., 2001; Shardanand and Maes, 1995). *"Social Comparison Theory"* (Festinger, 1954) distinguishes between *“physical reality”* and *“social reality”*: while the former is usually based on objective scales of reality with no need for other perspectives, the latter demands examination and comparison by others. According to the theory, *people choose similar ones to participate in the comparison process as only they can satisfy the function of a suitable social scale*. Two main assumptions underlie that theory:

- People have a drive to evaluate themselves.
- People tend to compare themselves to others and without the existence of objective scales for evaluation, mostly to similar ones to themselves.

According to Festinger (1954), only similar people are "chosen" to supply the scales of social reality as only they can satisfy the need for self evaluation. The term "similar ones" is not broadly discussed in the theory, but it is useful to distinguish between "*like-minded similarity"* (similar opinions) vs. *"personal similarity"* (for example: race, achievements, community):

- Rokeach and his Colleagues (1970) found that people tend to prefer others on the basis of similar opinions rather than on the basis of similar origin or race (Rokeach, 1968).
- Other researchers (Stein et al., 1965; Triandis, 1961) found that preference similarity is not obvious, for example: race-based similarity becomes a much more important factor than opinions-based similarity when the issue under concern becomes more important and intimate.

Hypotheses

This research aims to reveal a hidden angle of a new domain of collaborative filtering and recommender systems. Whereas most previous research has focused on items and algorithms, this research approaches the relatively less charted area of users' characteristics in recommender systems (recommendation seeker and provider). We try to establish a relationship between the perceived quality of the recommendation (expressed in terms of "user actions"- how a user actually follows the recommendation) and the formation of the advising group with user control over this process. The research method and our research tool enable us to record machine-collected data on how well recommendations are accepted implicitly, as well as the explicit self-reported 'likes' and 'dislikes'.

Research Questions

The research questions under investigation are:

1. Will people prefer to assume wider control over the recommendation process or to accept it as a "computerized oracle"?
2. Does the attitude of the recommendation seeker towards an advising group obey social rules (specifically the "social comparison" process), even when the user is aware that recommendations are processed and generated by a computerized system?
3. What are the characteristics of the 'friends' selected by the recommendation seeker to participate in his/her advising group when given an option to choose?

Hypotheses

The corresponding hypotheses are:

H_1: Recommendation seekers will prefer to use controlled 'friends groups' over automatically, machine-generated 'neighbors groups'.

H_2: Recommendations produced by user-controlled 'friends groups' will be more accepted and complied with by recommendation seekers than those produced by 'neighbors groups'.

H_3: Recommendation seekers will choose personally-similar[1] 'friends' for their advising group.

Methodology

We conducted a field study using QSIA – **Q**uestions **S**haring and **I**nteractive **A**ssignments system. QSIA was designed to harness the synergy of communities of practice and the implementation of online learning, teaching, testing and question-posing processes. We also developed a conceptual model that describes the user interaction with QSIA (figure 1). The model presents inputs, outputs and user's behavior regarding responses to recommendations from 'neighbors' and 'friends'. The system has been operational on the internet (http://www.qsia.org) since 2002 and access to collected data and logs will hopefully be made available to other researchers.

Research Tool – QSIA

QSIA is a collaborative system for collection, management, sharing, and assignment of knowledge items for learning. The system consists of various modules that allow the creation and editing of learning items, conducting online educational tasks and collaborative filtering module that assists users in filtering relevant information.

QSIA system is built on four conceptual pillars: Knowledge Generation, Knowledge Sharing, Knowledge Assessment, and Knowledge Management (Rafaeli et al., 2003).

Since its release, QSIA has provided important insights into knowledge sharing (Rafaeli et al., 2003), online question-posing (Barak and Rafaeli, 2004), communities of teachers and learners (Rafaeli et al., 2004), and the understanding of the potential of social recommender systems in support of E-Learning (Rafaeli et al., 2005).

Technical Overview

The system is Web-based with distributed architecture. The main technology used is Java, using java-beans JSP, Servlets and JDBC. The data is stored in a relational database. All the software components are free or open-source: Linux as the operating system, mySQL as the database, mm.mySQL as the JDBC driver and SUN JDK 1.3. All of our experiments were implemented using an IBM server (Intel Pentium 4 CPU, 1GHz, 1GB RAM) running Linux Red Hat O/S (version 7.0).

[1] "Personally"- in the sense of visible objective similarity (as opposed to "like-minded").

Conceptual Model of User - QSIA Interaction

We propose a five-stage conceptual model of user interaction with the recommendation module of QSIA, and define the variables, measures and involved computations accordingly. The model presented in the following figure is relevant in each case that a user (teacher or student) has to make a selection (filtering) from the system's database (for example: a teacher is selecting items for an assignment or a student is practicing prior to an exam).

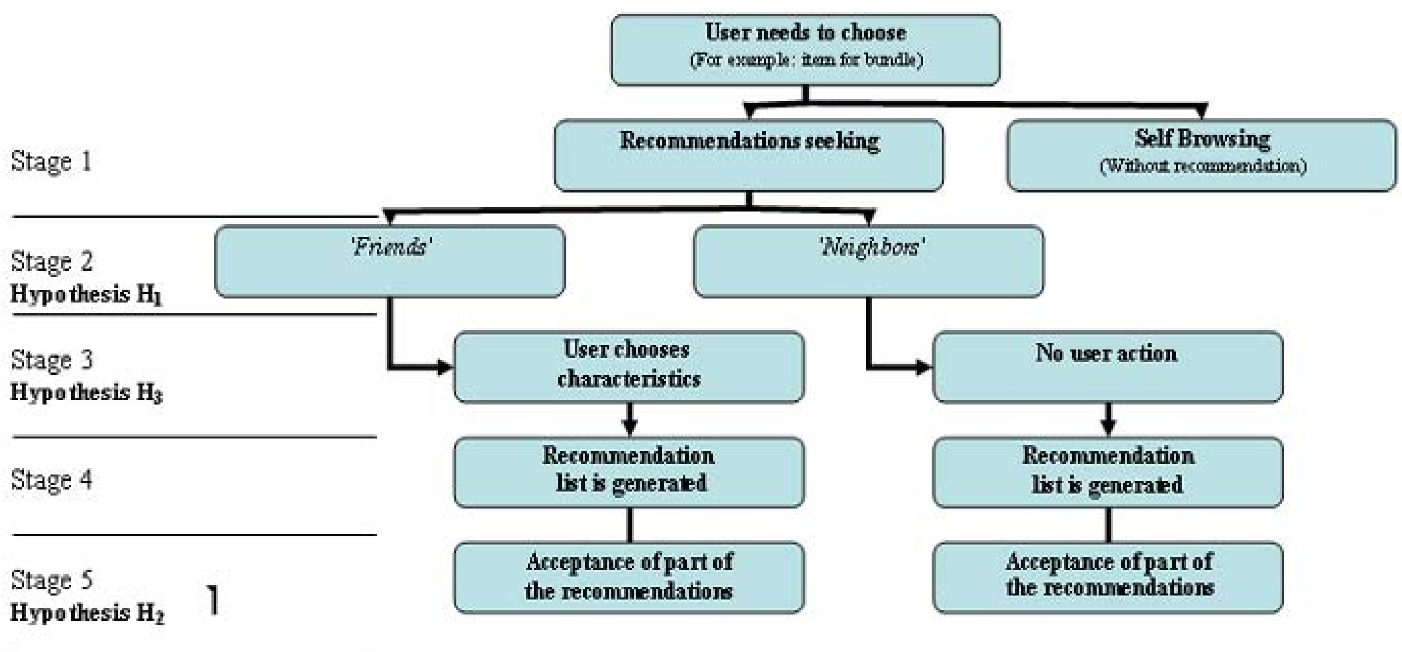

Figure 1. System's Recommendation Conceptual Model

To the left of the model we marked the stages and the corresponding hypotheses:

- *Stage 1* – The user faces two options: browsing and scanning the items to locate appropriate ones or using the recommendation features. This stage is not investigated in the current research though choices at this node are recorded for further processing.
- *Stage 2* – Out of all options of recommendations seeking, the user can choose to assume control of who advises: 'neighbors' or 'friends'. The default route is 'neighbors' (presented whenever the user does not choose to control this flow). This stage refers to hypothesis H_1, and it corresponds to an independent variable we shall later refer to as SoR (Source of Recommendation), which can assume one of two values: N_g ('neighbors group') or F_g ('friends group').
- *Stage 3* – This stage is only relevant in cases SoR= F_g (user chose to seek the recommendation of 'friends') and it involves the user's selection of the characteristics of the 'friends' to participate in the advising group.

This stage refers to hypothesis H_3 and it corresponds to an additional dependent variable of a three-dimensional array form we later refer to as friends' characteristics choice. It has a vector form of $\{fc_1, fc_2, fc_3\}$ where fc_j's are the user's relative grade level, group assignment and role (student/teacher).

- *Stage 4* – A list of top-N recommended items is generated either by neighbor's similarity $\{N_g\}$ or friend's choice $\{F_g\}$ and presented to the user.
- *Stage 5* – The user needs to finalize the process by deciding which items, if any, to accept and use out of the recommendation list: $\{N'_g\}$ when 'neighbors groups' are chosen or $\{F'_g\}$ for 'friends groups' choice. This stage refers to hypothesis H_2. We are mostly interested in the dichotomous categorization of the user's "likes" and "dislikes" regarding the items and less with the relevance of the ordering within the list.

Figure 2 presents the user's choice of friends' characteristics as described in stage 3 of the model (figure 1).

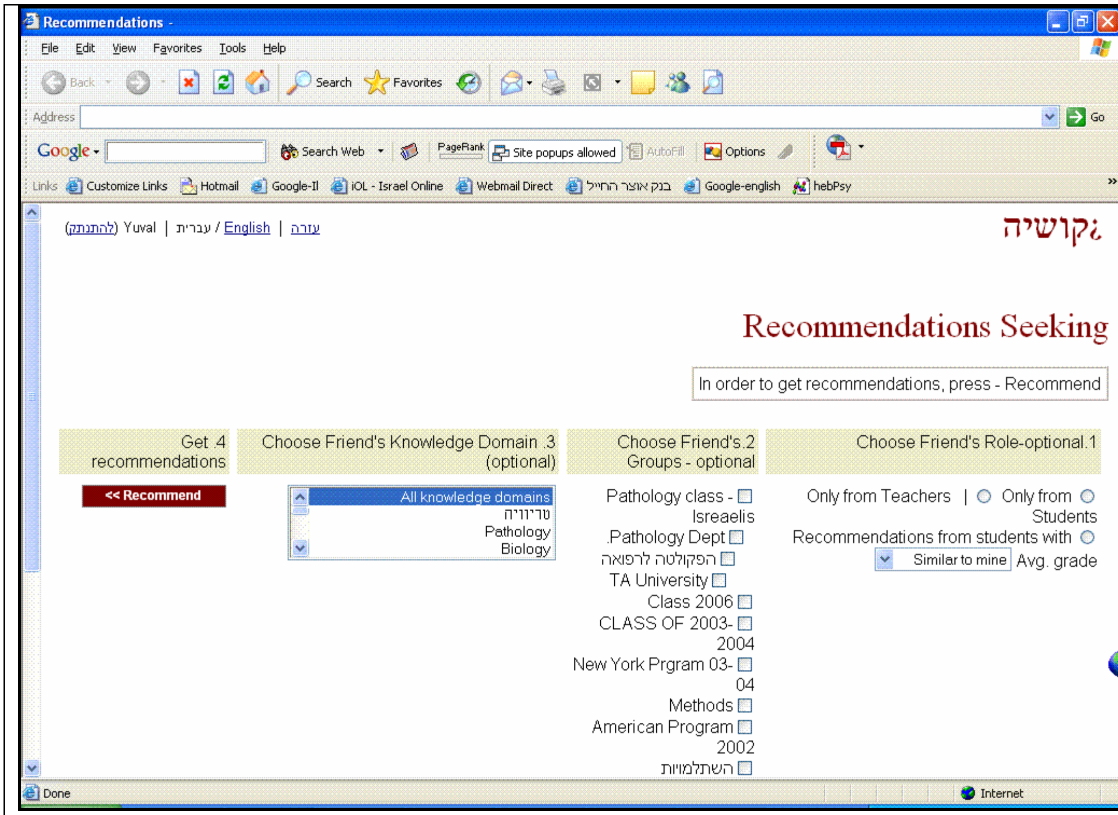

Figure 2. User's Choice of Friends' Characteristics: A Screen Capture

Procedure and Participants

This study includes data that was recorded in QSIA for over two years: from 2002 to 2004. Since it was launched, QSIA was implemented in about 20 institutions and courses in several countries and in various domains. For example:

- Electronic Commerce courses;
- Industrial Engineering and Management courses;
- Organizational Behavior courses;
- Foreign Language courses; and
- General and systematic Pathology courses.

Recorded Data

During the period of the field study (2002 to 2004), QSIA's database and logs presented us with the following figures:

- Number of users (teachers and students) – approximately 3000, most of them students.
- Number of items (either composed in QSIA or digitally imported) – approximately 10,000.
- Around 31,000 item-requests were served – mostly (refer to the conceptual model in figure 1) by self-browsing and a small portion by recommendations seeking ('friends' or 'neighbors').
- Number of item rankings – approximately 3000, evaluated by around 300 users.
- Number of study groups – 183.
- Number of knowledge domains – approximately 30.

When we filter out the data from recommendations seeking (either friends or neighbors), the figures narrow to 895 recommendation requests (818 by students and 77 by teachers) generated by 108 active users.

Statistical Analysis

We emphasize the following issues prior to analysis of the data:

- We analyzed logs and database of QSIA, our research tool which were collected over a period of more than two years (2002-2004) of free use of the system on the Web.
- Our field study was unobtrusive (Kalman and Rafaeli, 2005; Webb et al., 1966), and we did not manipulate any variables. Data on users' behavior was collected retrospectively

The main methods and tests that we used were: The *Wilcoxon Signed-Rank test*, the *Logistic Regression* (Agresty, 1996; Diggle et al., 1994), the *Generalized Estimating Equations (GEE)* for analysis of longitudinal binary data using logistic regression (Diggle et al., 1994; Hosmer and Lemeshow, 2000; Liang and Zeger, 1986) and the *Runs test* (Bradley, 1968) for establishing randomness of a binary process.

Hypothesis Testing Flow and Summary of Variables, Data and Analysis Methods

Figure 3 describes the procedure and conceptual positioning of the hypothesis testing flow, while table 1 summarizes the variables, data sources, formats and analysis methods.

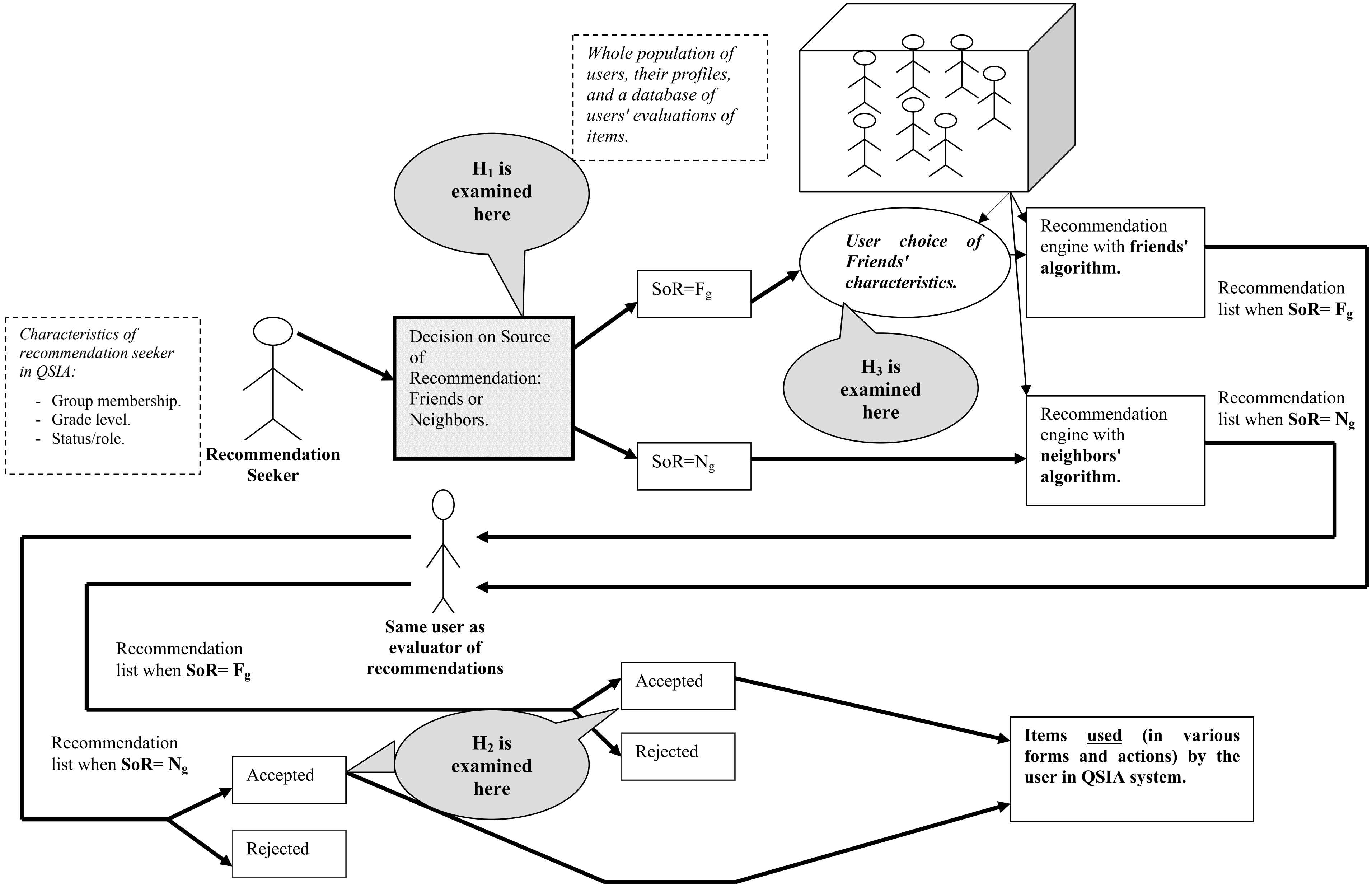

Figure 3. Testing of Hypotheses

Table 1. Summary of Variables, Data and Analysis Methods

Hypothesis	Independent Variables		Dependent Variables		Input Data	Statistical Analysis of Relationship	
	variable	Method of elicitation	variable	Method of elicitation	Format and type	Statistical Tests	Remarks
H$_1$: Recommendation seekers will prefer to use controlled 'friends groups' over automatically, machine-generated 'neighbors groups'.	**n$_j$** ≡ index number of the recommendation-seeking sequence for the jth user.	QSIA logs.	**SoR** $_i^j$ - source of recommendation (friends or neighbors). A categorical variable.	QSIA logs.	A table that details for each user the value of SoR in all instances of the user's recommendations seeking.	**Longitudinal tests** GEE model for longitudinal binary data in logistic regression. **Cross-sectional tests** • Classification of users using Bradley's runs tests. • Mean difference of proportions of friends and neighbors choices.	Longitudinal analysis is the primary method. Cross-sectional analysis is a supportive one.
H$_2$: Recommendations produced by user-controlled 'friends group' will be relatively more accepted and agreed with by recommendation seekers than those produced by 'neighbors group'.	**SoR** $_i^j$ - source of recommendation (friends or neighbors). A categorical variable.	QSIA logs.	R_i^j -number of items **rejected** by ith user in jth instance. A_i^j -number of items **accepted** by ith user in jth instance.	QSIA logs.	Two datasets (for SoR=F$_g$ and N$_g$) describing for each user, the total number of recommended items that $\sum_i R_i^j$ were rejected $\sum_i A_i^j$ and accepted	**User analysis** • Wilcoxon – for paired scores of users who asked both Fg and Ng. • Proportion test – for exclusive users who asked from one source only. **Item analysis** • Same items/same users. • Most frequent items.	
H$_3$: Recommendation seekers will choose personally-similar 'friends' to populate the advising group.	**SoR** $_i^j$ - source of recommendation. U$_{status}$ – user is a teacher or a student. $\overline{U}_{groups}$ – Vector of groups the user is a member of.	QSIA logs.	**Group$_c$**– group/s user chose to participate. **Grade$_c$**– grade's level user chose to participate. **Status$_c$**– roles user chose to participate.	QSIA logs.	Dataset presenting similarity between user's choices (of Group, Grades, Status) and user's profile - whenever friends' recommendations are requested.	• Proportion tests. .	There are alternative hypotheses to Status and Grade level choices.

Results

H_1: Preference for Using 'Friends Groups'

We filter out the records only to ones that are originated by recommendations (SOR_i^j = F_g or N_g), and analyze the 895 records of recommendations seeking that were produced by the 108 users. The proportion of the recommendations seeking roles (teachers/students) is described in the following table:

Table 2. Students and Teachers Participation in Recommendations Logs

	Users (N=108)	Records (N=895)
Students (or originated by students)	102	818
Teachers (or originated by teachers)	6	77
Total	108	895

The *"Depth of Use" (DoU_j), a variable that represents the maximum number of times that the j^{th} user had asked for recommendations*, varies widely as the next figure presents. It should be noted that there are some users that asked for large number of recommendations while many others presented us with a "cold start" behavior:

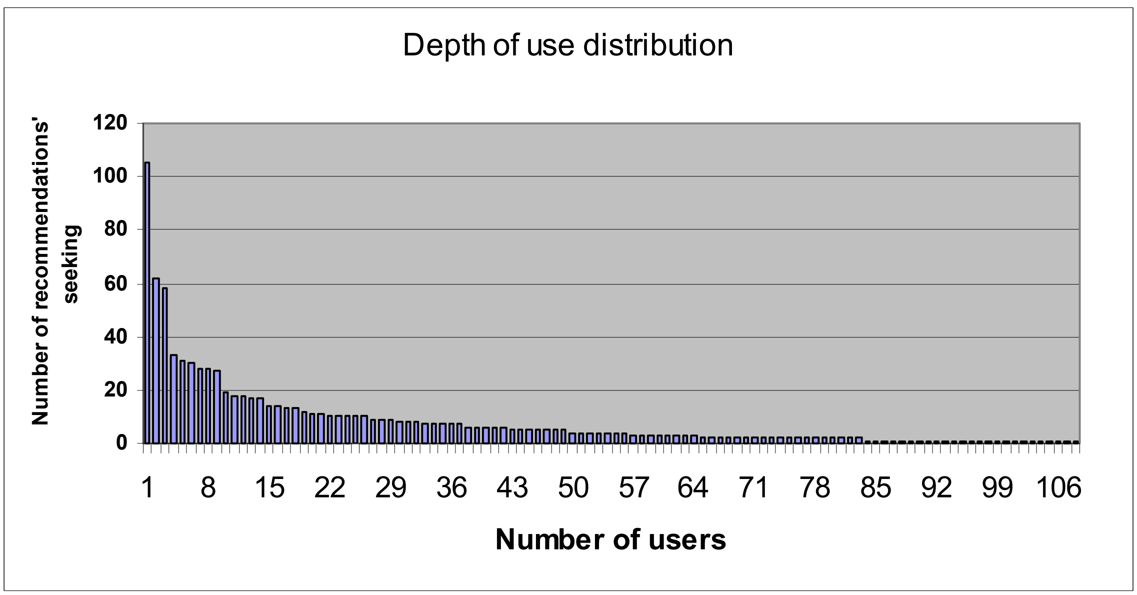

Figure 4. Depth of Use (DoU) Distribution

Longitudinal Analysis

Following our findings of DoU distribution, we plot only instances that consist of three or more data scores (DoU≥3), and the truncated data is presented in figure 5:

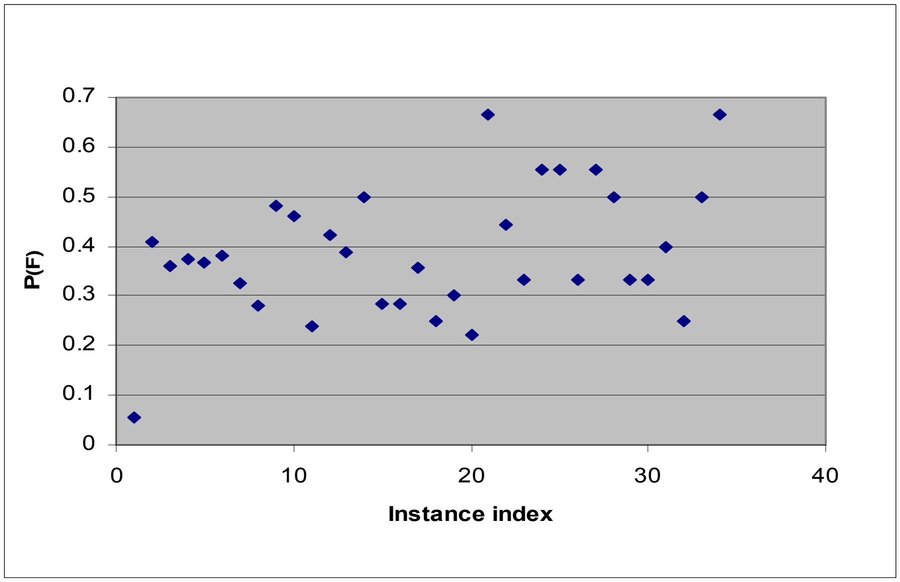

Figure 5. Ratio of Friend's Choice for DoU≥3

We now formulate our GEE model with logistic regression:

$$\textbf{Log}\ \frac{P(Fg)}{1-P(Fg)} = \beta_0 + \beta_1 \cdot DV_1 + \beta_2 \cdot DV_2 + \ldots\ldots + \beta_n \cdot DV_n = \beta_0 + \sum_{i=1}^{n} \beta_i \cdot DV_i$$

While the β_i are the coefficients of the logistic regression, DV_i is a *dummy variable* that equals "1" at a defined range of instances and "0" at all others. The dummy variables are complementary (together they cover all the range of instances) and mutually exclusive (only one dummy variable equals 1 at any instance). The reader should note that after the model converges and estimates the β_i, the estimated probability of 'friends group' choice ($P(F_g)$) is also known at the dummy variable's non-zero range by using the common logistic regression equations. The use of dummy variables in the GEE model with logistic regression becomes an accepted extension and enables inclusion of more than one independent variable to account for different behavior at different ranges of instances (Agresty, 1996, pp. 118-124; Hosmer and Lemeshow, 2000, pp. 31-42). Once the model is formulated, we perform the following procedure:

- Define the instance ranges for all the dummy variables (for example: DV_1=1 when $n \in \{2,5\}$, otherwise DV_1=0).
- Prepare the database for the model – in our case, all SoR's of all the users at each instance.
- Run the model until convergence.
- Examine the statistic of goodness-of-fit measure[2].

The model, among other parameters, reports the following:

- Estimated probability of friend's choice in each range (estimated $P_n(F_g)$ where $n \in \{ DV_i \}$).
- Confidence interval (95%) for the above estimation.
- Significance level (α) of β_i.

[2] Our measure for goodness-of-fit for the model is the Pearson Chi-Square calculated by the software.

We ran six models all with different ranges of dummy variables. We report the results of a *representative one*, model *GEE-20* that includes data only up to the 20th instance, where 75% of the observations cluster:

Table 3. Results of GEE-20 Model

Dummy variables (DV_i)	Dummy variables ranges of instances	Estimated friend's choice probability ($P(F_g)$)	Low 95% confidence interval	High 95% confidence interval	Logistic regression coefficients (β_i)	Significance level of β_i (α_i)
DV_0	{1}	0.05	0.02	0.12	β_0=-2.83	$\alpha \leq 0.0001$
DV_1	{2,5}	0.39	0.32	0.47	β_1=2.39	$\alpha \leq 0.0001$
DV_2	{6,10}	0.41	0.32	0.51	β_2=2.46	$\alpha \leq 0.0001$
DV_3	{11,15}	0.42	0.30	0.57	β_3=2.52	$\alpha \leq 0.0001$
DV_4	{16,20}	0.35	0.20	0.55	β_4=2.23	$\alpha \leq 0.0001$
Goodness Of Fit (Pearson Chi-Square)					1.0075 at DF=668	
N (number of observations in the dataset)					673	

We now plot the results of the GEE-20 model:

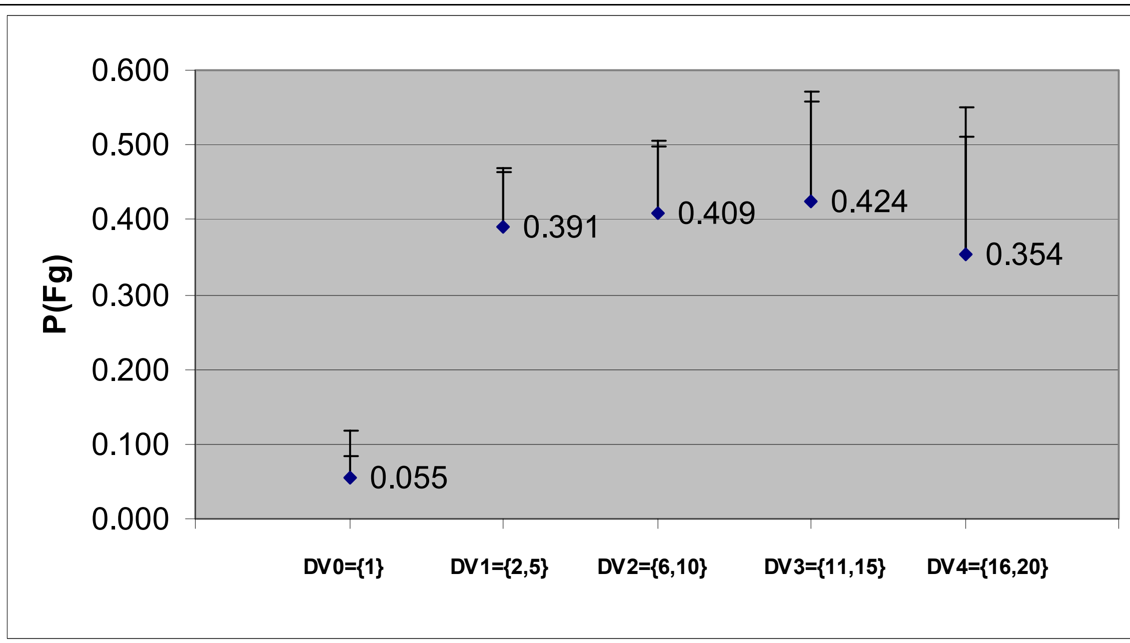

Figure 6. Graphic Results of GEE-20 Model

In all models, positive values of β_i suggest an increase in the probability of asking for 'friends group' recommendations as the instance index rises. The logistic regression coefficients are also significant. All models have Goodness-of-Fit of more than 95% according to the accepted Pearson Chi-Square measure.

Cross-sectional Individual Analysis

Although the longitudinal analysis was our primary method, as it examines the data along the correlated instances of recommendations seeking, we now consider the *users* as the unit of analysis. The following tests provide only corroborative evidence, mainly because they do not take into account the ordered sequential data and thus lose ageing effects (Diggle et al., 1994).

First, we run *proportions tests*: we test the ratios of choosing a 'friends group' (SoR=Fg) against the ratios of choosing a 'neighbors group' and examine the differences between the means. We run these tests with three datasets; each includes users with different threshold of DoU: min{DoU}=1, min{DoU}≥5, min{DoU}≥20.

The second method will apply the *Bradley's runs test* as a classification procedure. We halve the observations of each user and apply, where possible, the runs test to each half. In addition, whenever the test results in a non-random outcome, we test for significant dominance of either 'friends group' choice or 'neighbors group' choice. Our examined population will be *only* the users whose first half of observations is random and the second half is not random. "Success" is defined in terms of a user changing from a random behavior to a friend's preference. We then apply the Binomial test to check the deviation of "success" from chance occurrence.

Mean Differences

We detail the results of the first method in table 4:

Table 4. Mean Differences as DoU Increases

Min {DoU}	Measure	SoR = F_g	SoR = N_g	N_{users}	$N_{records}$	α (Wilcoxon, two-tailed)
1	Mean	0.27	0.73	108	895	α≤0.0001
	Mean difference ($E(F_g)-E(N_g)$)	**-0.46**				
5	Mean	0.37	0.63	49	780	α=0.001
	Mean difference ($E(F_g)-E(N_g)$)	**-0.26**				
20	Mean	0.43	0.57	9	402	α=0.44
	Mean difference ($E(F_g)-E(N_g)$)	**-0.14**				

We note the decreasing gap in the means as DoU rises and users with greater experience are included although significance level decreases due to a smaller dataset.

Runs Tests Classification

We intended to use the runs test as a classification procedure to categorize the users. We are interested in the class that showed a random behavior at the beginning and acquired a non-random behavior in the late sequence, specifically, those who chose 'friends' or 'neighbors' significantly more times.

The runs test requires a threshold of data of 1's and 0's to compute the critical runs for randomness. We used Bradley's table (Bradley, 1968, pp. 362) for small data that requires a minimum of 2/8, 3/5, 4/4, 6/4 combination of 1's and 0's respectively.

The requirement for sufficient sequences of recommendations seeking in both halves of the instances is approximately 10 (DoU≥10). Although only 19% of the population is valid for the classification, we present the following results:

Table 5. Results of Classification by Runs Test		
Characteristic	Number of users	Ratio of users
Total number of users	108	100%
Users without sufficient data for runs test	79	73%
Users with sufficient data for runs test	29	27%
Users that are excluded from the test set[3]	9	8%
Total users for analysis	20	19%
Random start pattern and final F_g dominance	*13*	65% (out of 20); 12% out of 108
Random start pattern and final N_g dominance	*7*	35% (out of 20); 6% out of 108
Binomial proportion test significance level	α = 0.13 (one-tailed)	

H_1: Preliminary Observations

In the following section, we briefly detail the main findings regarding the first hypothesis:

- The descriptive measures indicated a sharp decrease in the dataset volume concerning recommendations: only about 900 records out of 31,000 (~3%) were relevant. In addition, the Depth of Use (DoU) distribution revealed that although some users asked for many recommendations, the majority of users presented a "cold start" behavior (Mean=8.5, Std. Dev.=16.8, Median=3).
- *Longitudinal analysis* using GEE in logistic regression allowed us to examine changes in the probability of 'friends group' choice in increasing instances of recommendations seeking:
    - Our findings from six GEE models, all with sufficient Goodness-of-Fit measures ($\alpha<0.0001$), suggest that users increasingly seek 'friends group' recommendations over time.
    - Almost all the logistic regression coefficients (β_i) for all the examined ranges of instances were estimated as positive values, indicating an increase of probability of F_g as the instance index rises.
- *Cross-sectional analysis* was used as a supportive method, realizing that tendencies and ageing effects are results of longitudinal analysis. We incorporated a classification process using the Bradley's runs test for randomness and a test for the means of proportions of users' choices of F_g against choices of N_g:
    - We examined differences in the means of proportions for three datasets: users with DoU≥1, DoU≥5 and DoU≥20. The results, although presenting a greater proportion of 'neighbors groups' (N_g), showed that the difference of the means tends to decrease sharply (from -0.46 to -0.25 and to -0.14) with the rise of DoU, indicating that "experienced" users of the system choose 'friends group' significantly more than "new" users.
    - Bradley's runs test was our procedure to classify users into three categories, two of which interested us: users who started with a random behavior and ended with a non-random dominance of either F_g or N_g. Due to insufficient numbers of users with large enough DoU's to conduct the runs test, we ended with only 20 eligible users for analysis out of the total of 108 users (19%). The proportions of change from random behavior to 'friends' and 'neighbors' groups choice were 65% and 35% respectively (α=0.13).

[3] Either because of constant behavior in both halves or insignificant dominance of N_g or F_g.

H_2: Acceptance of Recommendations Produced by 'Friends Groups'

Acceptance and Rejection Elicitation in QSIA

For the purposes of measuring acceptance and rejection in QSIA with regard to our second hypothesis, we chose the immediate "usage action" as it has high validity of the subjective quality of the recommendation. In QSIA, once an item has been recommended, the user has three options regarding it:

- *Viewing the item* – when the user views the recommendation with no further action,
- *Applying the item* – when the user actually adds the item to a bundle for an assignment (examination, practice task, etc.), and
- *Experimenting with the item* – when the user "solves" the item using the simulation interface. From here two consecutive actions may result – a decision to apply the item (as described above) or to end the process.

For our data analysis, the following classifications were determined:

- *Acceptance of a recommended item* is counted whenever the recommendation seeker "applies the item" or "simulates an item".
- *Rejection of a recommended item* is counted whenever the recommendation seeker restricts the consecutive action to only "viewing the item".

Analysis and Results

Our complete record logs contain 895 instances of recommendations seeking from 108 users. For each user the list of recommended items may contain a maximum of 10 items and not less than two, which means that *theoretically*, the maximal volume of data is 8,950 (895×10). We were able to extract only 1,043 "user actions", however, mainly due to short recommendation lists and users that "aborted" the session during the process. The usable data were produced by 51 distinct users.

We present an overview of the dataset according to the origins of the records and the users (SoR=F_g or SoR=N_g) in table 6 and table 7:

Table 6. Acceptance Ratio – Neighbors

	Total acceptance $\sum_j A_i^j$	Total rejection $\sum_j R_i^j$
Value	305	436
Grand total	741 (by 38 users)	
Std. Dev.	12.6	27.6
Acceptance ratio	**41%**	

Table 7. Acceptance Ratio – Friends

	Total acceptance $\sum_j A_i^j$	Total rejection $\sum_j R_i^j$
Value	174	128
Grand total	302 (by 32 users)	
Std. Dev.	13.8	13.3
Acceptance ratio	**58%**	

User Analysis

The results of the "usage actions" (acceptances and rejections) for the *same users* who asked for recommendations from *both sources* are presented in the following table:

Table 8. Acceptance Ratios According to SoR		
	SoR=F_g	SoR=N_g
Number of records	264	377
Number of users	19	
Std. Dev.	0.29	0.3
Mean acceptance ratio	70%	56%
Mean difference	**14%**	
α (Wilcoxon, one tailed)	0.050	

The results show that acceptance ratio is 14% higher when users receive the recommendations from 'friends groups' rather than from 'neighbors groups' (α = 0.05). These results represent 641 usage records by 19 users who sought recommendations from both sources.

In the next procedure, the dataset includes users who asked for recommendations only from one source, either 'friends groups' *or* 'neighbors groups'. We report the following results for the exclusive users:

Table 9. Acceptance Ratios of Exclusive Users		
	SoR=F_g	SoR=N_g
Number of records	38	364
Number of users	13	19
Std. Dev.	0.38	0.33
Mean of acceptance ratio	70%	46%
Mean difference	**24%**	
α (Binomial, one tailed)	0.037	

For exclusive users (who "experienced" only one source of recommendation), the mean acceptance ratio for those who chose *only* SoR=F_g is higher by 24% from those who chose *only* SoR=N_g (α=0.037). Among users who asked recommendations from both sources, the mean acceptance ratio for those who chose SoR=F_g is higher by 14% from those who chose SoR=N_g (α=0.050).

Item Analysis

We first present the distribution of the number of times that items were recommended to the users:

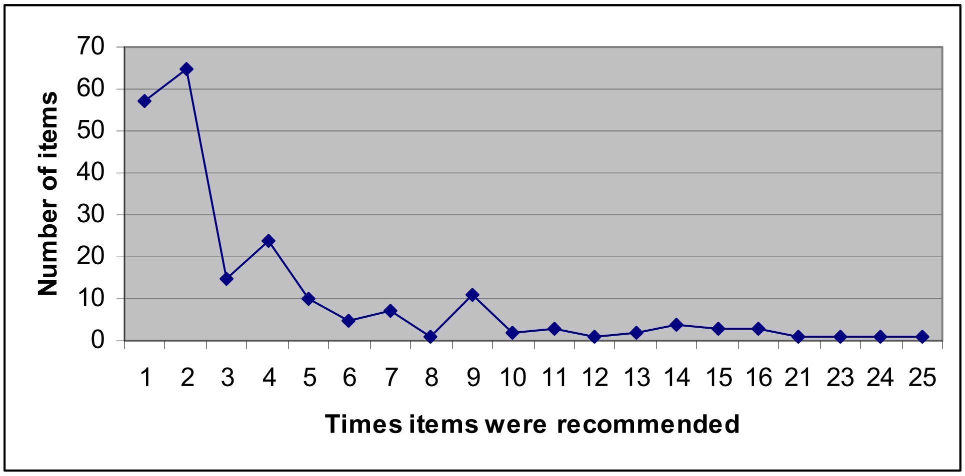

Figure 7. Distribution of Number of Times Items Were Recommended

Acceptance Ratios of the Same Items

We identified 36 items that have the following characteristics:

- These items were recommended to users by both 'friends groups' and 'neighbors groups'.
- Users acted upon theses recommendations, either by rejection or by acceptance in both scenarios of SoR's.

Our intention is to test the difference in acceptance and rejection ratios of the *same items*, when they were offered to users by 'friends groups' and 'neighbors groups', based on 394 usage records.

We present the results in the following table:

Table 10. Users' Acceptance Ratios for Items that were Offered by Both Sources

	Acceptance ratio	Rejection ratio	Total
SoR=F_g	142 (50.9%)	137 (49.1%)	279 (100%)
SoR=N_g	66 (57.4%)	49 (42.6%)	115 (100%)
Total	208 (52.8%)	186 (47.2%)	394 (100%)
Ratio difference	**6.5%**		
α (Pearson Chi-Square with continuity correction)	0.28		

We note that the acceptance ratio is 6.5% higher for the same items when recommended by a 'friends group', with a P-value of 0.28 (statistically insignificant).

Acceptance Ratios of the Most Frequently Recommended Items

We identified the items that were most frequently recommended. The threshold was 20 recommendations per item (approximately 5 times more frequent than the average recommendations of an item). We found four such items and computed for each of them the acceptance ratio of the item when offered by 'friends groups' and by 'neighbors groups'. We present the following results:

Table 11. Acceptance Ratios of the Most Frequently Recommended Items

	SoR=F_g	SoR=N_g
Number of recommendations	93	
Number of items	4	
Mean of acceptance ratio	63.9%	48.7%
Std. Dev.	0.033	0.056
Mean difference	**15.2%**	
α (Wilcoxon, one tailed)	0.034	

We note a significant difference in the acceptance ratio for the most frequently recommended items, depending on the source of recommendations group.

H_2: Preliminary Observations

In the following section, we briefly detail the main findings regarding the second hypothesis:

- The approach for testing H_2 was to examine "usage actions": how did users react in terms of acceptance and rejection to the recommendations they received, and was the reaction different depending on the source of the recommendation (SoR)?
- We tested two aspects of the data: for the user analysis, we calculated the same users' acceptance level of items when the items were offered by F_g and by N_g; for the item analysis, we compared users' acceptance ratios of the same items, depending on the items' SoR.
- The main findings from the *user analysis*:
  - We found a 14% positive significant difference in the mean ratios of acceptance towards F_g when we tested all users who had received and acted upon recommendations from both sources (F_g and N_g).
  - There was a higher positive significant difference in the mean ratios (24%, $\alpha = 0.037$) for users who received recommendations from only one source (either F_g or N_g).
- The main findings from the *item analysis*:
  - We examined all items that were offered to users from both sources (N=36). We found that, out of 394 records of "usage actions" of these items, the acceptance level was 6.5% higher when the recommendations were offered by 'friends groups' (P-value= 0.28).
  - We chose the most frequently recommended items (items that were recommended more than 20 times) and tested the difference in acceptance levels when the items were recommended by F_g and N_g. The acceptance ratio was 15.2% higher (N=4, $\alpha = 0.034$) when the same items were recommended by 'friends groups'.

H_3: Characteristics of the Chosen 'Friends'

QSIA enables users who choose 'friends group' recommendations to determine three characteristics of the recommenders in their group: status/role, grade level and group choice. This hypothesis examines the previously reviewed aspects of users initiated comparisons for each of these three characteristics.

We analyze a dataset of 335 records of 'friends group' recommendations seeking ($SoR=F_g$) from 32 users and examine their choices concerning each characteristic. The characteristics are considered statistically independent, except for the impossibility of specifying a *grade level* when the chosen *role* was "teacher", because teachers do not have associated grades in QSIA[4].

Group Choice

The group choice field includes 163 values from a possible 335. The results of proportion's tests of similar and dissimilar choices from the records that hold non-zero field values are presented in the following table:

Table 13. Group Choice Proportions

	Similar	Dissimilar
Proportion	88.3% (144 records)	11.7% (19 records)
Difference	76.6%	
Significance level (Sign test)	α<0.0001	

We found a significant preference of users to include members of their own group in their 'friends group', than members of other groups. This result is also important because we have the largest amount of data concerning group choice – almost half the users assigned a value to this characteristic.

Status/Role Choice

The status/role choice field includes 86 values from a possible 335, of which 5 were from teachers and 81 were from students. The results of the proportion's test are presented in the following table:

Table 14. Status/Role Choice by Teachers and Students

		User's choice		
		Teacher	**Student**	Total
User's role	**Teacher**	5.8% (5)	0% (0)	5.8% (5)
	Student	68.6% (59)	25.6% (22)	94.2% (81)
	Total	74.4% (64)	25.6% (22)	100% (86)
Difference in students' choices		**43%** α (sign test) < 0.0001		

4 Accordingly, a zero value in the grade level when the role choice was "teacher" is not considered a missing value.

We analyzed data only from students because teachers supplied only 5 records with this characteristic, without any choice in "student". The results present a greater choice of students in teachers' advice than in students' advice ($\Delta = 43\%, \alpha \leq 0.0001$).

Grade Choice

The grade choice field includes only 21 values from a possible 335, precluding a profound analysis. Our examinations show that 64 of the cases of "no choice" values ($grade_c$=0) are due to status/role choice of "teacher". Nevertheless, the figures are presented in the following table:

Table 15. Grade Choice Data

	Higher	Similar	Lower
Proportion	47.6% (10 records)	47.6% (10 records)	4.8% (1 record)
Total records with field values	21 (6.2%)		
Records with no grade choice due to choice of role="teacher"	64 (19.1%)		
Records with no grade choice	250 (74.6%)		
Total	335 (100%)		

Note that about half the time (10 records) users chose *higher level* and about half the time users chose *similar level*.

H_3: Preliminary Observations

In this section, we briefly detail the main findings regarding the third hypothesis:

- The approach for testing H_3 was to examine the users' choices concerning friends' characteristics which QSIA enables: Group, status/role, and grade level.
- There are many missing values in this part of our dataset: out of 335 records that originated by SoR=F_g, in almost half the cases users made a group choice, in another 25%, they made a role choice, and in only approximately 6% of the records, users made a grade choice (partially because "teachers" do not have associated grades).
- We analyzed the characteristics independently because we considered users' behavior towards them to be uncorrelated and because the data sparseness did not enable examination of internal correlations.
- We tested the observations against a different alternative hypothesis regarding users' behavior towards each characteristic:
  - Group – a significant preference for the similar group over other groups was found (76.6%, $\alpha<0.0001$).
  - Status/role – Teachers' recommendations were generally preferred to students' recommendation. Students asked for teachers' recommendations 43% more than for students' recommendations ($\alpha<0.0001$).
  - Grade – the data regarding relative grade choice was limited. Nevertheless, half of the requests were from students with "higher grade than mine" and the other half was from students with "similar grades to mine".

Discussion

Main Findings

First Hypothesis: ***Recommendation seekers will prefer to use controlled 'friends groups' over automatically, machine-generated 'neighbors groups'***

Supported: *Our findings suggest that users **do** develop a tendency to choose 'friends group' recommendations*. The probability of this tendency increases in as more recommendations are sought (In the GEE model: almost all $\beta_i>0$, $\alpha\leq0.0001$, Goodness-of-Fit>95%). Also, "experienced" users choose 'friends groups' significantly more than "new" users.

Second Hypothesis: ***Recommendations produced by user-controlled 'friends groups' will be more accepted and complied with by recommendation seekers than those produced by 'neighbors groups'***

Supported: *We found a 14% positive significant difference in the mean ratio of acceptance when we tested all users who had received and acted upon recommendations from both sources ('friends group' and 'neighbors group')*. There was a higher positive significant difference in the mean acceptance ratios (24%, $\alpha = 0.037$) for users who received recommendations from only one source (either 'friends group' or 'neighbors group'). Also, when the same items were offered to users from both sources (N=36), the acceptance level was 6.5% higher when the recommendations were offered by 'friends groups' (P-value= 0.28).

For the most frequently recommended items that were recommended by both 'friends group' and 'neighbors group', the acceptance ratio was 15.2% higher (N=4, $\alpha = 0.034$) for the same items when they were recommended by 'friends groups'.

Third Hypothesis: ***Recommendation seekers will choose personally-similar 'friends' for their advising group***

Partially supported: There were many missing values in this part of our dataset: in almost half the records users made a group choice, in another quarter of the cases they made a role choice, and in only approximately 6% of the cases did users make a grade choice. We analyzed the characteristics independently and found that in accordance with our hypothesis, users significantly prefer their own ***group*** over other groups (76.6%, $\alpha<0.0001$). ***Role***: students asked for teachers' recommendations 43% more than for students' recommendations ($\alpha<0.0001$). We explained it by an *alternative hypothesis* stating that students choose teachers' recommendations because of their role authority and knowledge expertise (Wyeth and Watson, 1971). The data regarding relative ***grade*** choice was limited, but we noted that half the requests were from students with "higher grades than mine" and the other half was from students with "similar grades to mine". The *alternative hypothesis* was that the "reference group" (a group that the person aspires to belong to) is comprised of students with "higher grades than mine" (Chapman and Volkman, 1939).

Weaknesses and Limitations of this Research

The limitations of this project are related to its uniqueness. Most important is the absence of a comparable field study. Additional weaknesses and limitations are:

- We did not collect self-report of user motivations for their actions, for example, by questionnaires. We collected data on the dependent variables and deduced the users' behavior accordingly.
- The participating populations, except in one case, were homogeneous: students and teachers of academic institutions.
- The characteristics of the advising group that were possible for the recommendation seeker to control were very limited: groups, grade level and role.
- The QSIA system applies recommender technology to a novel domain – knowledge items for distance learning and online tests - that is not "natural" for recommender systems. Consequently, we did not have other similar systems as a benchmark for these unique characteristics.
- The distribution and patterns of behavior were highly variable.

- Lack of data can, evidently, decrease the quality of recommendations, mainly because of the inability to match enough correlated neighbors to the particular user. The algorithm of 'friends group' lowers the number of members of the "advising group" even more because of the characteristics' constraints, and thus, may produce less favorable recommendations.

Summary and Conclusions

This research demonstrated that acceptance likelihood among users of social collaborative systems of the recommendations depends on the type of group that made the recommendations and on the users' involvement in the formation of that group.

The main new aspect of our findings is the relationship between the perceived quality of the recommendation, and the user's involvement in the formation of the advising group.

We reported the following support of the results in our hypotheses:

1. Over time, users increasingly sought their recommendations from 'friends groups' and the probability to do so even further increased with higher use of recommendations.
2. Users' acceptance level of recommendations was higher when they asked for 'friends groups' recommendations. In addition, the *same items* were more readily accepted when offered to the user by the 'friends group' than when offered by the 'neighbors group'. The difference in acceptance was higher for items that were recommended frequently.
3. We had insufficient data for some of the planned statistical tests of the third hypothesis. Nevertheless, we concluded that own group choice was the most important characteristic for users to assign to their advising group members.

References

Agresty, A. *An Introduction to Categorical Data Analysis*, Wiley, NY, 1996.

Balabanovic, M. "Exploring Versus Exploiting When Learning User Models for Text Recommendation," *User Modeling and User-Adapted Interaction* 8(1-2), 1998, pp. 71-102.

Barak, M. & Rafaeli, S. "Online Question-Posing and Peer-Assessment as Means for Web-Based Knowledge Sharing in Learning," *International Journal of Human-Computer Studies*, 61(1), 2004, pp. 84-103.

Bollacker, K., Lawrence, S., & Giles, L. "A System for Automatic Personalized Tracking of Scientific Literature on the Web," *in Proceedings of the fourth ACM conference on Digital libraries,* Berkeley, California, 1999, pp. 105 - 113.

Book Forager Recommender System, Available Online: http://www.branching-out.net/forager.

Bradley, J. V. *Distribution-Free Statistical Tests*, Prentice-Hall, NJ, 1968.

Breese, J. S., Heckerman, D., & Kadie, C. "Empirical Analysis of Predictive Algorithms for Collaborative Filtering," *in Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence*, Madison, 1998, pp. 43-52.

Chapman, D. W. & Volkman, J. "A Social Determinant of the Level of Aspiration," *Journal of Abnormal and Social Psychology* (34), 1939, pp. 225-232.

Cosley, D., Lam, S. K., Albert, I., Konstan, A. J. & Riedl, J. "Is Seeing Believing? How Recommender System Interfaces Affect Users' Opinions," *in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Ft. Lauderdale, Florida, 2003, pp. 585-592.

Delgado, J., Ishii, N., & Ura, T. "Intelligent Collaborative Information Retrieval Actively Learning to Classify and Recommend Documents," *in Proceedings of Artificial Intelligence (IBERAMIA'98*), 1998, pp. 170-182.

Diggle, P. J., Liang, K. -Y. & Zeger, S. L. *Analysis of Longitudinal Data*, Clarendon Press, Oxford, 1994.

Dijkstra, J. J. *On the Use of Computerized Decision Aids: An Investigation into the Expert System as Persuasive Communicator*,. Unpublished Ph.D. dissertation, University of Groningen, Groningen, Netherlands, 1998.

Dijkstra, J. J. "User Agreement with Incorrect Expert System Advice," *Behavior and Information Technology* 18(6), 1999, pp. 399-411.

Dijkstra, J. J., Liebrand, W. B. G., & Timminga, E. "Persuasiveness of Expert Systems," *Behavior and Information Technology* 17(3), 1998, pp. 155-163.

Festinger, L. "A Theory of Social Comparison Processes," *Human Relations* (7), 1954, pp. 114-140.

Fogg, B. J., & Tseng, H. "The Elements of Computer Credibility*," in Proceedings of CHI'99*, Pittsburgh, PA, 1999 pp. 80-87.

Freedman, S. G. "Asking Software to Recommend a Good Book," *The New York Times*, June 20, 1998.

Gates, C. S., Aggarwal, C. C., & Maglio, P. "Recommender Systems: Knowledge from Mining User Experiences," *Technical Report RC21447*, IBM Research, 1999.

Gefen, D. "E-Commerce: The Role of Familiarity and Trust," *Omega: The International Journal of Management Science* 28(6), 2000, pp. 725-737.

Geyer-Schulz, A., Hahsler, M., & Jahn, M. "MYVU: A Next Generation Recommender System Based on Observed Consumer Behavior and Interactive Evolutionary Algorithms," in *Data Analysis: Scientific Modeling and Practical Applications*, W. Gaul & O. Opitz & M. Schader (Eds.), Springer Verlag, Heidelberg, Germany, 2000, pp. 447-457.

Goldberg, D., Nichols, D., Oki, B. M., & Terry, D. "Using Collaborative Filtering to Weave an Information Tapestry," *Communications of the ACM* 35(12), 1992, pp. 61-70.

Goldberg, K., Roeder, T., Gupta, D., & Perkins, C. "Eigentaste: A Constant Time Collaborative Filtering Algorithm," *Information Retrieval Journal* 4(2), 2001, pp. 133-151.

Grasso, A., Meunier, J. L., & Thompson, C. "Augmenting Recommender Systems by Embedding Interfaces into Office Practices," *in Proceedings of the Hawaii International Conference on System Sciences*, Maui, Hawaii, 2000, pp. 247-275.

Herlocker, J., Konstan, J., & Riedl, J. "Explaining Collaborative Filtering Recommendations," *in Proceedings of the Conference on Computer Supported Cooperative Work*, 2000, pp. 241-250.

Hosmer, D. W. & Lemeshow, S. *Applied Logistic Regression*, Wiley, NY, 2000.

Jungermann, H. "Advice Giving and Taking," *International Conference on System Sciences (HICSS'99)*, Hawaii, 1999.

Kalman, Y. M. & Rafaeli, S. "Email Chronemics: Unobtrusive Profiling of Response Times," *in Proceedings of the 38th International Conference on System Sciences (HICSS 38)*, Big Island, Hawaii, 2005, pp. 108.

Karypis, G. "Evaluation of Item-Based Top-N Recommendation Algorithms," *Technical Report CS-TR-00-46*, University of Minnesota, Department of Computer Science and Army HPC Research Center, Minneapolis, 2000.

Konstan, J., Miller, B. N., Malt, D., Herlocker, J., Gordon, L. R., & Riedl, J. "GroupLens: Applying Collaborative Filtering to Usenet News," *Communications of the ACM* 40(3), 1997, pp. 77-87.

Lawrence, R. D., Almasi, G. S., Kotlyar, V., Viveros, M. S., & Duri, S. S. "Personalization of Supermarket Product Recommendations," *Data Mining and Knowledge Discovery* 5(1-2), 2001, pp. 11-32.

Lerch, F. J., & Prietula, M. J. "How Do We Trust Machine Advice?" in *Designing and Using Human-Computer Interfaces and Knowledge-Based Systems*, G. Salvendy and M. J. Smith (Eds.), Elsevier, Amsterdam, 1989, pp. 410-419.

Liang, K. -Y. & Zeger, S. L. "Longitudinal Data Analysis Using Generalized Linear Models," *Biometrika* 73(1), 1986, pp. 13-22.

Linton, F., Joy, D., Schaefer, H. P., & Charron, A. "OWL: A Recommender System for Organization-Wide Learning," *Educational Technology and Society* 3(1), 2000, pp. 62-76.

Lueg, C., & Landolt, C. "A Java-Based Approach to Active Collaborative Filtering," *in Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI'98)*, Los Angeles, 1998, pp. 319-320.

Maltz, D., & Ehrlich, K. "Pointing the Way: Active Collaborative Filtering," *in Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI'95)*, Denver, CO., 1995, pp. 202-209.

Moon, Y. "The Effects of Distance in Local Versus Remote Human-Computer Interaction," *in Proceedings of the CHI'98,* Los Angeles, CA., 1998, pp. 103-108.

Moon, Y., & Nass, C. "Are Computers Scapegoats? Attributions of Responsibility in Human-Computer Interaction," *International Journal of Human-Computer Studies* (49), 1998, pp. 79-94.

Murphy, D. S., & Yetmar, S. A. "Auditor Evidence Evaluation: Expert Systems as Credible Sources," *Behavior and Information Technology* 15(1), 1996, pp. 14-23.

Nass, C., & Moon, Y. "Machines and Mindlessness: Social Responses to Computers," *Journal of Social Issues* 60(1), 2000, pp. 81-103.

Oard, D. W., & Kim, J. "Implicit Feedback for Recommender Systems," in *AAAI Technical Report WS-98-08: Workshop on Recommender Systems*, July 27, Madison, WI., 1998.

Pescovitz, D. "Accounting for Taste," *Scientific American* 282(6), June 2000, pp. 44.

Preece, J. "Empathic Communities: Balancing Emotional and Factual Communication," *Interacting with Computers* 12(1), 1999, pp. 63-77.

Rafaeli, S., Barak, M., Dan-Gur, Y. & Toch, E. "Knowledge Sharing and Online Assessment," *in Proceedings of the 2003 IADIS E-Society Conference*, 2003, pp. 257-266.

Rafaeli, S., Barak, M., Dan-Gur, Y. and Toch, E. "QSIA - A Web-Based Environment for Learning, Assessing and Knowledge Sharing in Communities," *Computers and Education* 43(3), 2004, pp. 273-289.

Rafaeli, S., Dan-Gur, Y. & Barak, M. "Finding Friends Among Recommenders: Social and 'Black-Box' Recommender Systems," *International Journal of Distance Education Technologies (IJDET)* 3(2), 2005, pp. 30-47.

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

Resnick, P., Zeckhauser, R., Friedman, E. & Kuwabara, K. "Reputation Systems," *Communications of the ACM* 43(12), 2000, pp. 45-48.

Rokeach, M. *The Nature of Human Values*, Free Press, NY, 1968.

Rokeach, M., Smith, P. W., & Evancs, R. I. "Two Kinds of Prejudice or One," in *The Open and Closed Mind*, M. Rokeach (Ed.), Basic Books, NY, 1970, pp. 132-168.

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. "Item-Based Collaborative Filtering Recommendation Algorithms," *in Proceedings of the 10th International World Wide Web Conference (WWW10)*, Hong Kong**,** 2001, pp. 285-295. Available Online: http://citeseer.ist.psu.edu/sarwar01itembased.html.

Schafer, J. B., Konstan, J., & Riedl, J. "Recommender Systems in E-Commerce," in Proceedings of the First ACM Conference on Electronic Commerce, Denver, CO., 1999, pp. 158-166.

Shardanand, U., & Maes, P. "Social Information Filtering: Algorithms for Automating Word of Mouth," *in Proceedings of ACM CHI 95 Conference on Human Factors in Computing Systems,* Vancouver, Canada, 1995, pp. 210-217.

SkiMatcher Recommender System, Available Online: http://www.skimatcher.com.

Soboroff, I., Nichols, D., & Pazzani, M. "Workshop on Recommender Systems: Algorithms and Evaluation," *SIGIR Forum*, 1999, 33(1), pp. 36-43.

Stein, D. D., Hardyck, J. A., & Smith, M. B. "Race and Belief: An Open and Shut Case," *Journal of Personality and Social Psychology* (1), 1965, pp. 281-289.

Swearingen, K., & Sinha, R. "Beyond Algorithms: An HCI Perspective on Recommender Systems," *in ACM SIGIR 2001 Workshop on Recommender Systems*, New Orleans, Louisiana, 2001.

Terveen, L., & Hill, W. "Beyond Recommender Systems: Helping People Help Each Other," in *HCI in the New Millennium*, J. Carroll (Ed.), Addison-Wesley, Boston, 2001, pp. 487-509.

Terveen, L., Hill, W., Amento, B., McDonald, D., & Creter, J. "PHOAKS: A System for Sharing Recommendations," *Communications of the ACM* 40(3), 1997, pp. 59-62.

Traill, D. M., Bowskill, J. M., & Lawrence, P. J. "Interactive Collaborative Media Environment," *Journal of BT Technologies* 15(4), 1997, pp. 130-139.

Triandis, H. C. "A Note on Rokeach's Theory of Prejudice," *Journal of Abnormal and Social Psychology* (67), 1961, pp. 184-186.

Turing, A. M. "Computing Machinery and Intelligence," *The Journal of the Mind Association LIX* (236), 1950, pp. 433-460.

Ujjin, S., & Bentley, P. J. "Building a Lifestyle Recommender System," *in the Tenth International World Wide Web conference*, Hong Kong, 2001.

Webb, E. Campbell, D. Schwartz, R. & Sechrest, L. *Unobtrusive Measures: Nonreactive Research in the Social Sciences,* Rand McNally, Chicago, 1966.

Wood, J. V., & Taylor, K. L. "Serving Self-Relevant Goals through Social Comparison," in *Social Comparison Processes: Contemporary Theory and Research*, J. M. Suls & T. A. Wills (Eds.), Lawrence Erlbaum Associates, Hillsdale, NJ, 1991, pp. 261-285.

Wyeth, E. R. & Watson, W. C. "The Teacher in the Educational Hierarchy and the Teacher and the Curriculum," in *Teacher Pupil and Task: Elements of Social Psychology Applied to Education*, O. A. Oeser (Ed.), Tavistock Publications, London, 1971, pp. 7-29.