Collaborative Infomediaries and the Measuring Factors that Influence the Success of Infomediary

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摘要

在萬維網上-這個浩瀚的資訊海，使用者往往要花費上一定的時間去搜尋出他所需的資訊。針對這個問題，一種新的網上技術 - 資訊中介人，因而產生。本篇論文是有關一個爲投資者搜尋網上有關的中文財經資訊的“共協資訊中介人”(Collaborative Infomediary)系統。除此之外，我們亦建立了兩個工具去量度資訊中介人的成功關鍵因素。

隨著萬維網的普及化，很多報章出版社開始透過萬維網傳播新聞。但對於必須要找到有關的財經資訊去支持投資決策的投資者來說，無疑構成一個嚴重的問題。有見及此，我們的研究將針對這些投資者，設計一個名爲“共協資訊中介人”(Collaborative Infomediary)的系統，爲他們搜尋網上有關的中文財經資訊。這個系統引入了“用家共協”(across-user collaboration) 的特點，而這“共協”技術多作爲“內容導向資訊過濾”(Content Based Information Filtering) 互補的技術。我們這個系統，不單止利用“個人檔案”(Personal Profile)和“相關詞回饋”(relevance feedback)，也綜合了 “共協回饋”(collaborative feedback)；它結合了這三個技術爲用家搜尋出他所需的有關資料。我們亦進行了一個用家評估實

驗去測試“共協回饋”的成效。實驗證明添置了“共協回饋”的系統比原本沒有“共協回饋”系統優勝。

除此之外，由於互聯網技術的迅速發展及使用，再加上缺乏有關成功關鍵的概念基礎，現時仍沒有一套完善的“成功關鍵指標”去評估到底資訊中介人是否成功。關於這個問題，我們嘗試以 Keeney [38] 所提出的研究爲基礎，建立兩個工具去量度資訊中介人的成功關鍵因素。其中一個工具主要是量度影響用家使用資訊中介人系統的“中間目的”(means objectives)；另一個則是量度顧客認爲在使用資訊中介人系統時爲重要的“基本目的”(fundamental objectives)。在工具建立的研究過程中，我們以探索性因素分析 (exploratory factor analysis) 測試了工具的可信度 (reliability)，建構效度 (construct validity)，會聚及區別效度 (convergent and discriminant validity)。我們將逐一展示有關這些測試的證據。

最後，本論文將討論“共協資訊中介人”及“資訊中介人”之成功關鍵因素”的價值及未來之研究方向。

Abstract

Web users spend a lot of time searching for information on the World-Wide Web due to its massive content. A new web technology - Infomediary has emerged to tackle this problem. This thesis presents a Collaborative Infomediary system which helps investors to search for relevant Chinese financial news. Besides, in this research, we develop measures to evaluate the success of Infomediary model.

Many newspaper publishers have begun to disseminate the news through the World Wide Web owing to its popularity. This becomes a serious problem for the investors as they have to find relevant financial information for decision making on their investments. Hence, we present the *Collaborative Infomediary*, a system designed to help investors to search for Chinese financial news on the web. The system incorporates the "across-user collaboration" feature, which is often employed as a complementary technique to content-based information filtering system. Our system utilizes not only the individual user profiles and relevance feedback, but also integrates collaborative feedback from other users, to search for the relevant Chinese financial information on behalf of the users. Experiment was conducted to measure the performance of the collaborative feature of the system and user evaluation result has shown that the collaborative feature outperforms the original system with no collaborative feedback incorporated.

Currently, there is also the lack of measure to evaluate the success of Infomediary. This is due to the rapid development and use of Internet technologies and the lack of conceptual bases necessary to develop success measures. We therefore try to develop two instruments that together measure the factor that influence Infomediary success, based on the approach proposed in Keeney [38]. One instrument measures the means objectives that influence the use of Infomediary and the other measures the fundamental objectives that customers perceive to be important for the usage of Infomediary. We employed exploratory factor analysis to develop the instrument. During the instrument development process, evidence of reliability, construct validity, convergent and discriminant validity is presented for the hypothesized measurement models.

The thesis concludes with discussions on the usefulness of the *Collaborative Infomediary* and these *success measures* and also future research ideas.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction and Outline of the Dissertation

1.1 Collaborative Infomediaries

In recent years, the World Wide Web has become a major information dissemination channel. In order to cope with the user demand, many newspaper publishers are providing on-line news on the web in addition to their traditionally printed newspapers. Investors find financial information for their investment decision making through the World Wide Web. Despite information in the World Wide Web is ubiquitous to access, its massive amount make investors difficult to search out their information of interests. There calls for the provision of Infomediary which provides personalized recommendations for the investors and helps them to save their time and effort in searching for relevant interests.

Infomediary is a kind of agent. From the end user point of view, an agent is a program that assists people and acts on their behalf. In the system sense, it is a software object that is autonomous. Generally speaking, agents may be thought of as software entities that have the ability to undertake action autonomously in their particular embedded environment, according to a typically general set of requests or desired goals. Infomediary arises from a combination of the words ***info**rmation* and *inter**mediary***. An Infomediary is a Web site that gathers and organizes large amounts of data and acts as an intermediary between those who want the information and those who supply the information. An Infomediary works for the information provider as well as the information user. It plays a key role in getting the content owner in touch with the content user. From the user point of view, more users see each publisher's content than would be possible in a single-channel approach, as centralized search across thousands of titles contribute mightily to serendipity. For the publishers, Infomediary helps to distribute the content to information users. Instead of limiting content to those who know the path to a lone outpost of the web, the inclusion of content in a collection is accessible to a diverse range of users means wider readership. Infomediary products and services are thus, not just an agglomeration of articles. They are valuable part of the information chain [18]. Infomediary is a key player in the delivery of content, especially as that content makes a persistent migration from the print to electronic medium.

Though Infomediary provides more personalized results than internet search engine, its recommendation of result is only limited to reference from one's own profile and feedback for the searching of information. But actually there are many users who share common interests (*like-minded users*) in the information gathering process. In order to gain benefits from these *like-minded* users' experiences or recommendation, the concept of collaboration is first used by D. Goldberg [26] for filtering mails, and then is quickly applied in terms of product recommendation [61, 5]. We propose the use of collaborative feature in our Infomediary. Collaborative Infomediary works like recommender system which applies knowledge discovery techniques to the problem of making personalized recommendations for information, products or services during a live interaction, by producing a predicted likeliness score or a list of *top-N* recommended items for a given user. Basically, the recommendations or predictions provided by the Collaborative Infomediary are based on the opinions of other like-minded users. This kind of Infomediary adds values to the users in the situation when the amount of on-line information is too enormous for the user to survey it by himself or herself.

1.2 Measuring Factors that Influence the Success of Infomediary

As aforesaid in the previous section, with the rapid growth of Internet and the improved accessibility of web information, the problem of information overload in our modern life exacerbates. Infomediary then emerges to help users save the time in searching information. It serves the function as simplifies, abstracts, reduces, merges, and explains data [75]. According to a definition by King [39], an Infomediary is a new Internet business model that applies to firms that help customers deal more efficiently and effectively with online vendors. In e-commerce, it functions as a third party provider of unbiased information and a business matchmaker. Also, the term *infomediary* was coined in 1998 to describe an independent third party which acts as a buffer between the Internet and the consumer [43]. An Infomediary also provides vendors with consumer information to help them focus on products and services customers want. For example, MySimon, BizRate, and Yahoo shopping are infomediaries for general products such as books, computers; while Expedia, Priceline, and Travelocity are infomediaries for flight tickets, hotels and rental cars. While Infomediary becomes an important business protocol in e-commerce there is yet no metric to measure the success of Infomediary.

Since the early days of management information systems, researchers have been seeking reliable means and ways of measuring system success. It has long been identified as one of the most critical issues in Information System (IS) Management. *End-user IS satisfaction (EUISS)* has always been tied as the contributing factor for system success evaluation [4, 24, 23]. According to Au et al. [2],which conducted an review of end-user information system satisfaction, based on an extensive literature search of over 50 EUISS related papers, *user satisfaction* is the most widely used measure of IS success. It is the high degree of face validity of satisfaction, due to reliable instruments having been developed by past researchers, and also the conceptual weakness of most other measures, that makes satisfaction sufficed as the measuring factor. It is also a critical construct in the sense that it is often used as a surrogate of management information system success [4], and also it is related to other important variables in system analysis and design. Au et al. [2] also found out from the review of past research studies that sometimes sound technical system performance not necessarily guarantee high user satisfaction. Most systems fail to meet the objectives and aspirations held for them, not because they are not technically sound, but because psychological issues are not addressed during the development, implementation and use of the system.

Though there are many user information satisfaction (UIS)and end-user computing satisfaction (EUCS) measures to evaluate information system success, they are not suitable measures for Infomediary success evaluation. The reason lies in the difference in role of an individual customer to that of an organizational end user. Measures of user information satisfaction developed for this kind of conventional data processing environment or end-user computing environment may no longer be appropriate for the web information system, especially Infomediary. The reason is UIS and EUCS instruments focus primarily on general or specific user information within an organization rather than on customer satisfaction with regard to e-commerce. To mitigate this problem, Keeney [38] attempted to find out the value of Internet commerce to the customer. Further to this, Torkzadeh and Dhillon [69] developed an instrument to measure the success of Internet Commerce. However, this instrument is not yet tailor-made for Infomediary.

1.3 Thesis Contributions

In this thesis, we present a Collaborative Infomediary for retrieving online Chinese financial information provided by newspaper publishers. Such Collaborative Infomediary is a software agent that utilizes user profile, user relevance feedback and feedback from like-minded users to search information of interests for the investors. User profiles are used to capture basic knowledge of user reading preferences. User feedback is utilized to gain more specific knowledge about the user priorities related to semantics of the rated news articles. Collaborative feedback is also integrated to take into account the recommendation from like -minded users. This Collaborative Infomediary, while in comparison to the traditional internet search engine, provides more personalized results and gathers other recommendations for the users. Besides, in an attempt to understand how the users value most in using Infomediary, the thesis also describes the development of an instrument for measuring the success factors with Infomediary. We are to evaluate a set of constructs that influence users in Infomediary. The constructs are built primarily on concepts proposed by Keeney [38] but with modification from review on other literatures to count in success factors, to generate extensive list of success factors for Infomediary.

The research goals were to develop instruments that:

1. measure success factors of Infomediary
2. identify the multidimensional nature of these factors
3. demonstrate reliability and construct validity, and
4. are appropriate for use by academics and practitioners alike.

1.4 Thesis Organization

The rest of the thesis is composed as follows. Chapter 2 gives a review on the related work which describes previous researches on collaborative recommender systems and the various techniques employed in these systems. Chapter 3 illustrates the designs and algorithms used in our Collaborative Infomediary. Evaluation methodology and results of our Infomediary are then presented in chapter 4. In chapter 5, there is the review of the related work on measuring user satisfaction and success of Infomediary. Chapter 6 presents our research approach on measuring the factors that influence the success of Infomediary. Followed is chapter 7 on the data analysis and results for the measurement model. We draw the conclusions and present some ideas for future work in Chapter 8.

Chapter 2

Related Work on Collaborative Infomediary

2.1 RECOMMENDER SYSTEM - Infomediary

Searching Information on the web has become a daily activity for all people. With the plethora of information on the web, information filtering is an area getting more important. Hence, systems which can provide personalized recommendations to their users have gained a lot of interest in recent years. These are called recommender systems. They were originally defined as ones in which 'people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients' by Resnick and Varian [54]. According to Burke [13], the term now has a broader connotation, 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. It bears the criteria of "individualized" and "interesting and useful" that separate itself from information retrieval systems or search engines. In Cheung and Tian [19], they also refer to the systems which aim at filtering out the uninterested items (or predicting the interested ones) automatically on behalf of the users according to their personal preferences. There have been a number of prototypes developed for recommending items such as books [46], web pages [34], Usenet articles [40], music [61], and many more. As described in section 1.1 Infomediary is an agent acts as buffer between the Internet and the user. It attempts to customize information on the Internet according to the user interests. It works like recommender system. Users make requests and it provides recommendation back. Generally, the recommendation techniques employed by common recommender systems can be classified into four types: utility-based, knowledge-based, content-based and collaborative [13].

2.1.1 Utility-based recommenders

Both *utility-based* and *knowledge-based* recommenders do not attempt to build long term generalizations about their users, but rather base their evidence on an evaluation of the match between a user's need and the set of options available. *Utility-based* recommenders make suggestions based on a computation of the utility of each object for the user. The system attempts to derive a user-specific utility function and then employs constraint satisfaction techniques to locate the best match. This approach calculates a utility value for objects to be recommended, and in principle, such calculations could be based on functional knowledge. However, existing systems do not use such inference, requiring users to do their own mapping between their needs and the features of products, either in the form of preference functions for each feature or answers to a detailed questionnaire [29]. Since utility-based techniques require that the system build a complete utility function across all features of the objects under consideration, it can incorporate many different factors that contribute to the value of a product. However, this creates a burden of interaction on the user to indicate all his preferences. Moreover, the systems suggestion ability is static, i.e. they do not learn. [13]

2.1.2 Knowledge-based recommenders

Knowledge-based recommendation attempts to suggest objects based on inferences about a user's needs and preferences. The system has functional knowledge: the knowledge about how a particular item meets a particular user's need and applies the knowledge to match the item with the user's need, and can therefore reason about the relationship between a need and a possible recommendation. Several systems (for example [60]) employ techniques from case-based reasoning for knowledge-based recommendation. Knowledge-based recommender systems do not have *ramp-up* or *sparsity* problems, since they do not base recommendations on accumulated statistical evidence. However, they are prone to the drawback: the need for knowledge acquisition. They also suffer from the same weakness as utility-based recommenders, i.e. lack of learning ability. But it has beneficial characteristic.

It is appropriate for casual exploration, because it demands less of the user than utility-based recommendation. [13]

2.1.3 Content-based recommenders

In *content-based* system, the objects of interest are defined by their associated features. It learns a profile of the user's interests based on the features present in objects the user has rated [13]. It attempts to recommend items similar to those a given user has liked in the past [5]. Schafer et al. [59] calls this 'item-to-item correlation'. Cheung and Tian [19] defines content-based systems as those extract items' characteristics and compare them with users' interest profiles for predicting the users' preferences over the items. A number of techniques have been used. The simplest one is the use of keyword matching, with the user profile represented by appending keywords of highly rated items' descriptions. More sophisticated techniques include the use of ontology-based similarity measures [9] and rule-based systems [8]. Content-based techniques suffer from *new user problem* in that they must accumulate enough ratings to build a reliable classifier. They also have the *limited content analysis* problem that they are limited by the features that are explicitly associated with the objects they recommend. Besides, generally speaking, item characterization may need a variety of domain-specific feature types, each associated with their own feature extraction techniques. Even with a properly chosen representation, content-based recommender systems can only recommend items similar to what the user has indicated interest before, without any clue to explore other potential interests of the user. This is commonly called the *over-specialization* problem [5]. The recommended items need to be diversified in order to mitigate the problem. With the help of user ratings sharing, the collaborative approach provides another powerful means for the recommendation diversification.

2.1.4 Collaborative recommenders

Burke [13] quoted *collaborative recommendation* as probably the most familiar, most widely implemented and most mature of the technologies. Goldberg et al. [26] define collaborative filtering as collaboration in which people help one another perform filtering by recording their reactions to documents they read. Chau et al. [17] further explain that collaborative filtering systems will recommend a set of documents or items that may be of interest based on the user's profile and other users' interests and past actions, when user performs a search. Hence, *Collaborative recommendation* (or *collaborative filtering*) predicts user preferences for items in a word-of-mouth manner [19]. That is, user preferences are predicted by considering the opinions (in the form of preference ratings) of other "like-minded" users. They aggregate ratings or recommendations of objects, recognize commonalities between users on the basis of their ratings, and generate new recommendations based on inter-user comparisons. Schafer et al. [59] calls this "people-to-people correlation". An active user is matched against other users in the database to discover *neighbors*, who have demonstrated similar taste to active user historically. Items that the neighbors liked are then recommended to the active user. As preference ratings are used instead of domain-specific features, the applicability of collaborative filtering is more universal [19]. Also, the great power of the collaborative approach relative to content-based ones is its cross-genre or 'outside the box' recommendation ability. It has been very successful in both research and practice, and in both information filtering applications and E-commerce applications. Examples of collaborative filtering or recommender system include GroupLens [40], Fab [5], Ringo [61], Siteseer [57], Referral Web [37] and PHOAKS [67].

Ringo in [61] is a recommender system for music albums and artists. Similarity of users is computed based on the profile that is constituted by the user ratings on the music. Siteseer [57] is a web-page recommendation system that uses an individual's bookmarks and the organization of bookmarks within folders for predicting and recommending relevant pages. The system treats bookmark as implicit declaration of interest in the underlying content and user grouping behaviour as indication of semantic coherency or relevant grouping. The overlap of URL of each person's folder with that from other people accounts for the similarity. However, this kind of implicit behaviour may not necessarily be an accurate measure for user interests, as a result, not an appropriate base for similarity comparison. The PHOAKS [67] system tries to mine recommendations of Web resources (in terms of URL links) from Usenet news messages. The rationale behind is just to count a mention of URLs as a recommendation. However, this system is short of personalization and all users receive the same recommendation despite the difference in interests. While the Referral Web [37] is a system for reconstructing, visualizing, and searching social networks on the World-Wide Web. The author asserts that the social network is an important source for information dissemination.

The social network is modelled by a graph, where the nodes represent the individuals, and an edge between nodes indicates direct relationship between the individuals. The system uses the co-occurrence of name in close proximity in any documents publicly available on the Web as evidence of a direct relationship. However, this kind of data mining user social network requires some clear definition of what suffices to a direct relationship between users.

2.1.5 Hybrid recommenders

Hybrid recommender systems combine two or more recommendation techniques to gain better performance with fewer of the drawbacks of any individual one. Most commonly, collaborative filtering is combined with some other techniques in an attempt to avoid the ramp-up problem [13]. For instance, Fab [5] employs the hybrid approach from both content-based and collaborative recommendation. The users request recommendations and the ten highest-ranking Web pages are shown according to their profile. The ten highest-ranking pages are recommended according to how well the content of the page match the user profile. This is the content-based part of the system. Then, the users rate each page according to how well it matches their interests. They provide the feedback with 7 points on ordinal scale from excellent to terrible. The collection and selection agents use this feedback to refine their profiles (relevance feedback). Additionally, any highly rated pages are passed directly to the user's nearest neighbors - other people with similar profiles. Another system -EntreeC [13] employs hybrid of knowledge-based recommendation and collaborative filtering to recommend restaurants for the users.

2.2 Types of Collaborative Filtering

There are two main types of collaborative filtering algorithm defined by Breese et al. [10]: *memory-based* and *model-based* methods.

2.2.1 Memory-based methods

As per Breese et al. [10], *memory-based* algorithms operate over the entire user database to make predictions. The algorithms compute the proximities of opinions (in the form of preference ratings) between the targeted user and each of the others in the entire database, and then estimate the preferences of the targeted user for the unrated products accordingly. The proximities of opinions define the *like-mindedness* between users, i.e. the similarity between users. The preference of a user for an unrated item is then predicted by summing up the contributions of other users for the same item, and weighted on the basis of a user similarity measure. Hence, the introduction of the weighting allows a user to take into consideration more the opinions (i.e. preference ratings) of the "like-minded" users [19]. The success of this approach relies on the availability of a sufficiently large set of quality preference ratings. In practice, it is hard to require individual users to provide too many preference ratings before using the system, at least it is hard when they first register onto the system. So, providing accurate recommendations under the sparse data condition is one of the main challenges for building collaborative recommender systems [40]. One solution is to use *model-based* methods.

2.2.2 Model-based methods

Model-based method computes some compact abstraction of user preference patterns for interpolating missing data [19]. This collaborative filtering approach uses the user database to estimate or learn a model, which is then used for predictions [10]. Model based systems attempt to learn a model from the user ratings and then use this model in item recommendation. Various model-based methods have been proposed in the literature, including a variety of clustering models [8, 71], classifier models [51], Bayesian networks [10], and dependency networks [30]. However, the model-based methods like the clustering model, suffer from the problem of being not as personalized as the memory based approach. The reason behind is that the cluster model generally tries to recommend a set of documents to a cluster, in which the user belongs to, instead of making recommendations to individual users.

2.3 Similarity Measures

As discussed in section 2.2.1, memory-based methods employ different similarity measures to define the "like-mindedness" between users. The user similarity function among users affects the other users' contributions in predicting preferences of the target user on the unrated item. Thus, the recommendation accuracy highly relies on how the underlying similarity measure is defined. Memory-based methods are similar in spirit to the *k-nearest neighbour* (kNN) approach which is common used in the pattern recognition community. It is more popular and widely used in practice. The *nearest neighbor algorithm* has the advantage to rapidly incorporate the most up-to-date information, but the search for neighbors is slow in large databases. There are a number of proximity estimates used in previous researches to find out the "like-minded" users, i.e. the neighbors: Pearson Correlation (the most common) [40, 53], Mean Square Differences [61], Constrained Pearson Correlation [61] and Vector Based Cosine approach [58, 10].

Mean Squared Differences Algorithm *Mean squared differences* algorithm is used by Shardanand and Maes [61] to measure the degree of dissimilarity between two user profiles, which consists of ratings on music. It is computed as the average of squared differences between ratings in profiles. However, this kind of distance metrics is not useful as preference ratings are not objective measurements with random fluctuations, but are subjective ones provided by different users. It is easy to understand that different users subconsciously apply their own biases in providing preference ratings. Even for the same range of preference ratings, identical rating scores given by two different users, say one being critical and the other being generous, could mean quite different extents of preference. Pearson correlation coefficient is the most commonly proposed statistics to get rid of this effect caused by individual bias [19].

Pearson Correlation Coefficient The *Pearson correlation coefficient*, being the most common [53, 40], makes use of negative correlations as well as positive correlations to make predictions. To present the Pearson correlation coefficient computation, let S_{xy} be the set of all items co-rated by both users x and y, i.e., $S_{xy} = \{s \in S \mid r_{x,s} \neq \emptyset \ \& \ r_{y,s} \neq \emptyset\}$, where $r_{x,s}$ represents the rating of user x on item s. The Pearson coefficient for the user similarity between user x and user y is computed as:

$$sim(x,y) = \frac{\sum_{s \in S_{xy}} (r_{x,s} - \bar{r_x})(r_{y,s} - \bar{r_y})}{\sqrt{\sum_{s \in S_{xy}} (r_{x,s} - \bar{r_x})^2} \sqrt{\sum_{s \in S_{xy}} (r_{y,s} - \bar{r_y})^2}} \tag{2.1}$$

GroupLens in [40] is a system for collaborative filtering of netnews – electronic news articles adopted this measure for computation of user similarity. The authors built the GroupLens system on the assumption that people who agreed in the past will probably agree again and then use opinions that other people who have already rated the articles. However, the argument may be flawed in the sense that the similarity between user ratings on past news articles, not necessarily implies similar preference on current or future news articles for fast changing nature of news.

Constrained Pearson Correlation Coefficient With the standard Pearson correlation coefficient, any data whose trend is positively sloped will have a positive correlation, irrespective of position on the scale. In order to tackle this problem, Shardanand and Maes [61] makes use of another similarity measure – constrained Pearson correlation by modifying the Pearson correlation. This algorithm is motivated by the fact that ordinary correlation may not capture similarity, since shifting ratings by a constant leaves correlation unchanged. This variant takes positivity and negativity of ratings into account. The value above a chosen cutting point, z is positive while below it is negative. The constrained Pearson coefficient between users x and y is then computed as:

$$sim(x,y) = \frac{\sum_{s \in S_{xy}} (r_{x,s} - z)(r_{y,s} - z)}{\sqrt{\sum_{s \in S_{xy}} (r_{x,s} - z)^2} \sqrt{\sum_{s \in S_{xy}} (r_{y,s} - z)^2}} \tag{2.2}$$

Cosine-based In various literature [58, 10], cosine-based approach is employed for user similarity computation. In this approach, the two users x and y are treated as two vectors in m-dimensional space, where $m = |S_{xy}|$. Then, the similarity between two different users is measured by computing the cosine of the angle between these two vectors:

$$\begin{aligned} sim(x,y) = \cos(\vec{x}, \vec{y}) &= \frac{\vec{x} \cdot \vec{y}}{|\vec{x}| \times |\vec{y}|} \\ &= \frac{\sum_{s \in S_{xy}} r_{x,s} r_{y,s}}{\sqrt{\sum_{s \in S_{xy}} r_{x,s}^2} \sqrt{\sum_{s \in S_{xy}} r_{y,s}^2}} \end{aligned} \tag{2.3}$$

where $\vec{x} \cdot \vec{y}$ denotes the dot-product between the vectors $\vec{x}$ and $\vec{y}$.

2.4 Prediction algorithm

After the similarity between users is computed, in memory based collaborative filtering, the most important step in a collaborative filtering system is to generate the output interface in terms of prediction. That is to compute the value of unknown rating $r_{x,s}$ for user x on item s. The prediction is always as an aggregate of the ratings of some other (usually the N most similar) users for the same item s. The most common aggregation approach is to use the weighted sum in formula 2.4, where $\hat{C}$ denotes the set of N users c' that are most similar to user c and who have rated item s (N can range from 1 to the number of all users) [1].

$$r_{c,s} = k \sum_{c' \in \hat{C}} sim(c, c') \times r_{c',s} \tag{2.4}$$

$$r_{c,s} = \bar{r_c} + k \sum_{c' \in \hat{C}} sim(c, c') \times (r_{c',s} - \bar{r'_c}) \tag{2.5}$$

Multiplier k serves as a normalizing factor and is usually selected as $k = 1/\sum_{c' \in \hat{C}} |sim(c, c')|$. However, this weighted sum method does not take into account the fact that different users may use the rating scale differently. This is the *individual bias* problem. The *adjusted* weighted sum, as shown in formula 2.5, has been widely used to address this limitation [12, 10, 53]. In this approach, instead of using the absolute values of ratings, the weighted sum uses their deviations from the average rating (own bias) of the corresponding user.

2.5 User Profile

In collaborative recommendation system, a personalization component is always built to store the user characteristics so as to form a basis for user similarity computation. Buono et al. [12] defines user profile to be a representation, which is possibly structured, of that user, in order to take into account his or her needs, goals and interests. User profile is then a restructured representation of the user information needs. A typical profile in a collaborative system consists of a vector of items and their ratings, continuously augmented as the user interacts with the system over time. In some cases, ratings maybe binary (like/dislike) or real-valued indicating degree of preferences [13]. In the past researches in collaborative filtering, the user profile was generated either on the basis of user-specified keywords [51] or from the key-terms extracted from documents proposed by user's relevance feedback [49].

2.6 Relevance Feedback

Relevance Feedback is the process for which the user feedback preference on specific content on each article is gathered. The merit of relevance feedback lies on the ground that it enables the recommender system to refine its representation of the user's query. In a collaborative system constructed by Balabanovic and Shoham [5], relevance feedback operates based on the algorithm that if users liked a page, weights for the words extracted from it can be added to the weights for the corresponding words in the user profile. But how would the relevance feedback be generated? From the literature, the opinions of users can be obtained *explicitly* from the users or by using some *implicit* measures. Explicit rating is defined as which the user consciously express his preference on a discrete numerical scale. Fab [5] and GroupLens [53] collect explicit evaluations from users, i.e. users explicitly assigned rating on a numeric scale based on how much they like the items. Implicit rating is to interpret user behavior or selection to impute a vote of preference. Resnick and Varian [54] found out that several systems gather implicit evaluations: GroupLens [40] monitors users' reading times, PHOAKS [67] mines Usenet articles for mentions of URLs; and Siteseer [57] mines personal bookmark lists. Semantic ratings from user are also captured by some systems [13]. It is a kind of rating that tells the system not just the user's preference - thumbs up or thumbs down - but also the reason behind the rating: too expensive, not fancy enough etc.

2.7 Comparison basis for user similarity

There are different comparison basis for similarity formulation. Current researches [73, 76, 50] tried to exploit the similarity of users from the user information access patterns, which is kind of users implicit behaviour, such as comparing the user's navigation path and the access patterns of past users. The user information access patterns can be categorized into the usage, frequency, viewing-time and viewing-order based measures. This approach is adopted on the basis that human information access patterns tend to follow a continuity of interests. But as aforesaid, the implicit ratings are not accurate capture of user interests. Another comparison basis is to associate the user together based on the user's ratings on past articles [40, 10]. But this kind of comparison made the memory-based methods prone to *sparsity* and *first-rater* problem. In these kinds of collaborative system, there is the assumption of presence of large enough number of customers willing to provide preference ratings to many products. However, this is not essentially the reality. Since the effectiveness of the comparison relies heavily on the degree of overlapping among the user ratings, accuracy of the predicted ratings degrades significantly when the available ratings are sparse (sparsity problem). An extreme form of the sparsity problem is the first-rater problem, which arises when a new item appears. Our collaborative system will alleviate this limitation.

Chapter 3

Research Methodology

It will be an extension of previous research where an intelligent agent monitors the posting of web information providers and utilizes user profiles and user feedback to learn user preference. The system then searches for Chinese financial news online on behalf of users. The existing system utilizes the techniques of content-based and relevance feedback filtering. The main research focus here is to incorporate a new add-in, the collaborative agents. Our collaborative agent is "autonomous" and "cooperative" in the sense that it records down the user preference and automatically finds out the "like-minded" users for the active users and then provides recommendation of news article with reference to the feedback provided by similar users. Our system is then a hybrid of *content-based filtering*, *relevance feedback filtering* and *collaborative filtering*.

The recommendation of news articles will be based on the

1. active user profile which is a structure representation of basic knowledge about user preferences (*Content-based filtering*);

2. user feedback, semantics of user rated news articles (*Relevance Feedback filtering*);and

3. new add in feedback from similar users is also incorporated (*Collaborative Filtering*).

3.1 Collaborative Infomediary System Design

3.1.1 System Functionalities

The Collaborative Infomediary offers user great benefits in time saving of searching for relevant financial news online. The system automatically search news on user's behalf. User can choose to view the financial news of the current day, or search for past news. Before the system grasps the news for him, user has to provide his preferences: specifies his interests in the user profile, declares whether to choose his own collaborators or the system chooses for him, provides domain weighting on how to find the collaborators and relative importance between profile and feedback in searching for the relevant news, etc. Section 3.6 depicts the user interfaces on how user navigates in the system to search for relevant financial news.

3.1.2 Overview of System Design

The system architecture of the Collaborative Infomediary consists of seven components: fetching, indexing, content based filtering (user profile), data mining engine, relevance feedback filtering (user feedback), collaborative filtering, and search engine. The collaborative filtering is the main focus of this research. Figure 3.1 shows our system architecture.

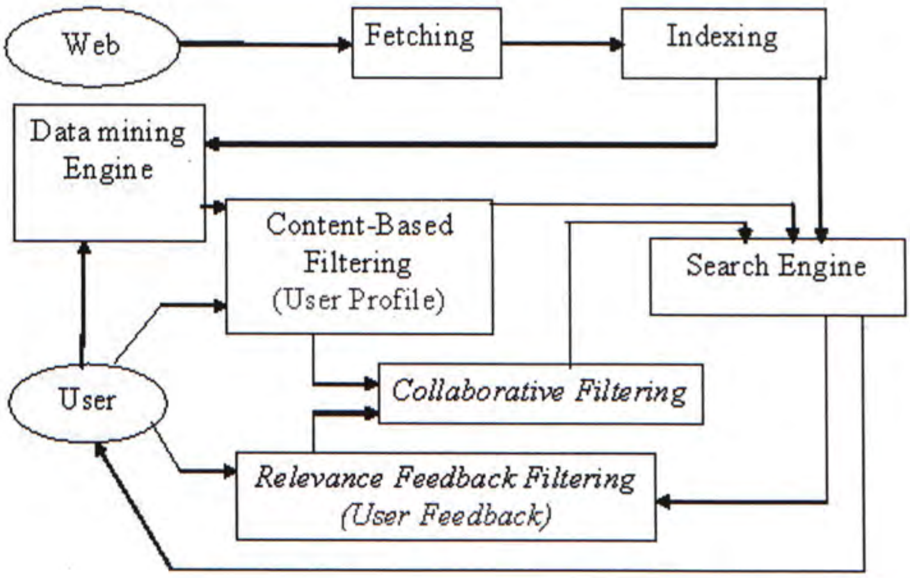

Figure 3.1: System Architecture of Collaborative Infomediary

The *fetching* component fetches the daily financial news documents from the Web site of news sources. Each fetched news article with it title, date, news source, and the published date will be stored in the database for reference. All the contents of document will be passed to the next component for further processing. The *indexing* component will index all the wordings in news articles and extract the important features (keywords) to represent each article. These keywords are then used for filtering news articles. *Content-based filtering* gathers basic information of user preferences on five domains: source of news, region of news, categories of industries, listed companies and user specified keywords. These user preferences are stored in the user profile. *Data mining* engine finds out the probabilities of a news article belongs to our defined seven industries. *Relevance feedback filtering* captures the degree of the user interests in a news article where user explicitly rates that article. The *collaborative filtering* component computes the user similarity and aggregates the other users' opinions weighted on the user similarity to predict the active user preference on news articles. For each rated article, either rated by the active user or his collaborators, we utilize the Jaccard's score to determine its relevance with the newly fetched articles. The *search engine* retrieves the relevant documents and calculates the document ratings based on the keywords extracted in indexing, user profile, user feedback and collaborator feedback. However, if the user is a first time user, no past feedback could be provided for rating calculation. The article will then presented in descending order of relevance (document scoring) to the active user.

3.2 User Profile

User profile is used to capture knowledge on user preferences, areas of interests and reading habits. A good user profile not only increases the precision of retrieval but also narrows down retrieval scope that directly reduces processing time. Since the user of Collaborative Infomediary purposefully searches for financial news that help them to make investment decision, our system uses five domains in user profile to capture the user's information needs. In the existing system, the user profile contains the "Gathering data", i.e. sources and regions of news articles, the "Personal data", i.e. the user specification about the industries, companies to which the news belongs and also user specified keywords. The user feedback is also included. As compared to other systems mentioned in section 2.5, the user profile design in our system captures a rich source of profile information for a known user, instead of only keywords.

3.2.1 Sources of news articles

We include this domain since different users have different preferences for the information providers. Although similar content is reported by different information providers, investors find some of the authors in some particular newspapers more credible and their comments are more helpful in their decision making process. Our system currently uses six newspaper sources on the Internet. The sources are listed in Table 3.1. A slider on the graphical user interface is provided for the users to submit their confidence level on news source domain, w_s, ranged from very bad to excellent for each newspaper source. [(Very bad|Bad|Average|Good|Excellent)(討厭|不好|一般|喜愛|很酷) record as (0.2|0.4|0.6|0.8|1.0) by the system] (For User Interface, please refer to section 3.6.1). w_{si}, is then the captured confidence level for the user on a newspaper source i where $i \in (1, 2, 3, 4, 5, 6)$.

3.2.2 Regions of news

As Hong Kong is an international financial center, besides local financial news, news from China and international will also affect the Hong Kong stock market. In most of the newspaper sources, the financial news is classified into three regional categories: (i) local (本地), (ii) China (内地), and (iii) international (國際). For different users, news from different regions may affect their investment by different degree. The user can choose his confidence

	Newspaper		URL
S1	Ming Pao	明報	http://www.mpfinance.com/
S2	Oriental Daily	東方日報	http://www.orientaldaily.com.hk/fin/
S3	AppleDaily	蘋果日報	http://appledaily.atnext.com/template/apple/sec_main.cfm?sec_id=15307
S4	Sing Pao	成報	http://app.singpao.com/
S5	Wen Wei Po	文匯報	http://www.wenweipo.com/catList.phtml?cat=006FI
S6	The Sun	太陽報	http://the-sun.com.hk/

Table 3.1: Chinese newspaper sources

level on region domain, w_r, ranged from very bad to excellent on these three regions through the graphical user interface. Similar to the source domain, the system will then record w_{ri}, user confidence level on region i where $i \in (1, 2, 3)$. [(Very bad|Bad|Average|Good|Excellent)(討厭|不好|一般|喜愛|很酷) captured as (0.2|0.4|0.6|0.8|1.0) by the system](For user interface, please refer to section 3.6.1)

REGIONS = (R1, R2, R3)

R1 = Local Financial News

R2 = China Financial News

R3 = International Financial News

3.2.3 Categories of Industries

The 7 major industries in Hong Kong are available for users to choose: Real Estate (地產), Finance (金融), Manufacturing (製造), Public Utility (公用), Resources (資源礦產), Service (服務) and Technology (資訊科技).

Data mining method (Bayesian classification) is used in previous study to find out the most representative keywords of these industries, rather than assign a keyword into a particular industry. Informative keywords, which can be used to discriminate the news into different industries efficiently, are identified using information gain. In this domain, user can select the preferred industries. The system then records the binary values either 1 or 0 if user select or not select that industry respectively. (For user interface, please refer to section 3.6.1)

INDUSTRIES = (I1, I2, I3, I4, I5, I6, I7)

I1 = Real Estate,

I2 = Finance,

I3 = Manufacturing,

I4 = Public Utility,

I5 = Resource,

I6 = Service,

I7 = Technology

3.2.4 Listed Companies

Our system provides a list of company names and their corresponding codes in the Hong Kong Exchange for users to select the listed company. Again, the system records the binary values either 1 or 0 if user select that company or not select. (For user interface, please refer to section 3.6.1)

3.2.5 User-specified Keywords

User can specify his or her interests by supplying specific keywords. (For user interface, please refer to section 3.6.1) These Internet terms can be person names, locations, or company names etc, in any number of Chinese characters or English words.

3.2.6 User Profile Scoring ($Score_{profile}$)

This is the content-based filtering module of the Collaborative Infomediary. The Personal User Profile Score, $Score_{profile}$, is the original score of news articles which is used to indicate the news article goodness in terms of matching with the user profile. This formulation, as shown in formula 3.1 , is already built in the existing system. It is the accumulation of the relative weight scores obtained from preference on sources of newspapers, regions of news and keywords matching score earned from categories of industries, listed companies and user-specified keywords. The score of categories of industries are calculated by summation of the normalized score $NSCORE_k$ of chosen industries k, and multiplied to the weight w_i. The score of listed companies and user-specified keywords is calculated by dividing the frequency of the corresponding keywords f_{uj} by its cardinalities C_u, and multiplying to its corresponding weight w_u.

$$Score_{profile} = w_s \times w_r \times (w_i \sum_k NSCORE_k + w_u \frac{\sum_j f_{uj}}{C_u}) \tag{3.1}$$

where w_s and w_r are the weights of the sources of newspaper and the regions of news for a particular news article provided by the user through the user interface as described before. w_i is the weight of categories of industries, w_u is the weight of listed companies and user specified keywords. In the system, w_i is set to 1 while w_u is set to 3, to amplify the effect of user specified keywords and listed companies relative to industries. This is based on the rationale that the domain of user specified keywords and listed companies are more specific than the categories of industries. Since a news article may be classified into more than one category of region, w_r is taken as the average of importance of news the users selected. For example, if $w_{r1}^x = 0.2$,$w_{r2}^x = 0.4$ for user x, and the news article belongs to both Local and China news, w_r is 0.3.

3.3 User Feedback

This is the relevance feedback filtering. We capture the user feedback for past news articles. The user provides explicit ratings instead of implicit ones. We adopted explicit feedback as it would be a more accurate capture of users' preferences. It is made on a 5 points basis scale. [(Very bad|Bad|Average|Good|Excellent)(討厭|不好|一般|喜愛|很酷)] record as (0|0.25|0.5|0.75|1.0) by the system. (For user interface, please refer to section 3.6.2)

3.3.1 Scoring formulation for feedback ($Score_{feedback}$)

The rating score of newly fetched articles by our infomediary also relies on the score on each rated article in the relevance feedback provided by both users and collaborators. We will discuss in later section how the system finds the collaborators. The semantic relevance feedback score, $Score_{feedback}$, also takes account of similarity between the newly fetched articles and articles rated by users and his collaborators in relevance feedback. It is computed as in formula 3.2.

$$Score_{feedback} = \sum_{j=0}^{n} (w_{bj} \times J(a_i, b_j)) \tag{3.2}$$

where w_{bj} is a converted user ratings based on active user and similar user feedback, computed as in formula 3.3. $J(a_i, b_j)$ is the Jaccard's score between the newly fetched article a_i and the rated article b_j , n is the total number of articles that have been rated. It is a similarity function between the newly fetched article and the rated articles.

The weight of rated article,w_{bj} is computed using modification of weighted sum method (discussed in section 2.4) as follows:

$$w_{bj} = \frac{w_{user} \times (F_{user} - \bar{F}_{user}) + \sum w_{peer} \times (F_{peer} - \bar{F}_{peer})}{w_{user} + \sum w_{peer}} + \bar{F}_{user} \tag{3.3}$$

F_{user} is the active user rating on that news article and F_{peer} is the collaborator rating on that news article. $\bar{F}_{user}$ indicates the active user average ratings on the set of m documents rated by him while $\bar{F}_{peer}$ indicates the collaborator ratings on the set of p documents rated by him or her. Hence, $(F_{user} - \bar{F}_{user})$ and $(F_{peer} - \bar{F}_{peer})$ show the tendency of respectively the active user feedback and the collaborative user's as compare to his own mean ratings. We set w_{user} which indicates the weight of active user, as one if the active user rated that article or zero if he did not. w_{peer}, weight of peer, is based on overall user similarity, r_{xy} ,which we will explain the formulation 3.8 later in section 3.4. If a user does not provide feedback for a news article,w_{user} in both the nominator and denominator will be set to 0 for that user. This is based on the rationale that if a user does not provide feedback for that article, he/she should not have any impact on its rating.

3.4 User Similarity

This is the collaborative filtering technique we incorporated into our system. Since the rating score of newly fetched articles by our infomediary also relies on the feedback provided by collaborators, before we can aggregate the collaborators' feedback, we have to determine the 'neighbours' for the active user. This is the most important step of our collaborative agent. Our system computes the user similarity using comparison between user profiles for the following reasons. First, it is *simple* and *efficient*. Since there is only one profile for each user, it is rather easy to compare the user profiles and the result can be calculated in a relatively short time and precomputed in off-line mode. In this system, it is believed most of our users are long-term investors. Even for those speculators, it is believed that they got a pool of stocks or derivatives, which they are most familiar with. In this sense, users will not change their profiles so frequently. So, the effort on calculation will not be so intensive. Second, since there is a small chance that the users read the same documents and our database is dynamic, the user similarity between user ratings approach is not suitable for our system. It will cause the *sparsity problem*. This approach also suffers from the weak grounds that similarity of opinions on past articles not necessarily implies similar preference on current or future news articles for news content can be absolutely different everyday. Lastly, the user profile is a structured and comprehensive representation of user preference, it can truly reflect user information needs. Hence, user profile forms a sound basis for user similarity computation in our system.

The user similarity computation relies on the user profile, which consists of 5 domains: Source, Region, Categories of industry, Listed companies in Hong Kong and also User Specified Keywords.

3.4.1 Source

The 6 online sources that we fetch the news from are listed in table 3.1. We employed the most popular Constrained Pearson Correlation Coefficient to compute the similarity between user x and user y on this domain - source of news article, based on the confidence levels submitted by the users.

$$r_{xy}^{S} = \frac{\sum_{i}^{6}(w_{si}^{x} - 0.6)(w_{si}^{y} - 0.6)}{\sqrt{\sum_{i}^{6}(w_{si}^{x} - 0.6)^{2}}\sqrt{\sum_{i}^{6}(w_{si}^{y} - 0.6)^{2}}} \tag{3.4}$$

where w_{si}^{x} is the confidence level of user x on source si. 0.6 is chosen as the "cutting point" as it indicates "average". This cutting point is added to introduce the positivity / negativity of ratings between users and the range of r_{xy} is from -1 to 1.

3.4.2 Regions of news

We categorized the financial news into three regional categories: (1) local; (2) China; and (3) international. We also use Constrained Pearson Correlation Coefficient, to compute the similarity between user x and user y on this domain.

$$r^R_{xy} = \frac{\sum_i^3 (w^x_{ri} - 0.6)(w^y_{ri} - 0.6)}{\sqrt{\sum_i^3 (w^x_{ri} - 0.6)^2}\sqrt{\sum_i^3 (w^y_{ri} - 0.6)^2}} \tag{3.5}$$

where w^x_{ri} is the importance indicated by user x on region ri. Again, 0.6 is chosen as the "cutting point" and the computed similarity runs from -1 to 1.

3.4.3 Category of Industries

In this domain, user can select the preferred industries, either "yes" or "no". As there is no positivity or negativity between user ratings, the cosine measure is employed, we represent the user preferences as vector of 7 dimensions on the 7 industries: Real Estate, Finance, Manufacturing, Public Utility, Resources, Service and Technology. The similarity is computed by the cosine of angle between the vectors of two users.

$$r^I_{xy} = \cos(\vec{I_x}, \vec{I_y}) = \frac{\vec{I_x} \cdot \vec{I_y}}{\left|\vec{I_x}\right| \times \left|\vec{I_y}\right|} \tag{3.6}$$

where $\vec{I_x}$ is the vector representing the user preference on industries of news. This measure takes the value from 0 to 1.

3.4.4 Listed companies in Hong Kong stock market and User-specified Keywords

In this domain, user can select the preferred listed companies, either "yes" or "no" and also key in his specified keywords. Based on the same rationale as in industry domain, as there is no positivity or negativity between user ratings, we also employ the vector space model. We compute a combined cosine for the domains Company and User-specified Keywords

$$r_{xy}{}^{k'} = \cos(\vec{k'}_x, \vec{k'}_y) = \frac{\vec{k'}_x \cdot \vec{k'}_y}{\left|\vec{k'}_x\right| \times \left|\vec{k'}_y\right|} \tag{3.7}$$

where $\vec{k}'_x$ is the vector representing the user specified keywords and keywords for listed companies. The value ranges from 0 to 1.

3.4.5 Overall Similarity

The overall similarity between two users x and y is the combined similarities on the above five domains:

$$r_{xy} = (w^S \times r^S_{xy} + w^R \times r^R_{xy} + w^I \times r^I_{xy} + w^{k'} \times r^{k'}_{xy}) \tag{3.8}$$

The w^S, w^R, w^I and $w^{k'}$ are the user defined weights of the five domains which are normalized and is on a 5 points basis scale of (0.2, 0.4, 0.6, 0.8, 1). (For user interface, please refer to section 3.6.1). This computed r_{xy} is used for the previously mentioned computation of scoring formulation for feedback in formula 3.3. The $w_{k'}$ will be doubled in order to take into account that k' is contributed by two domains. In the case where user set the weights on all domains for collaborator computations to "很酷", then $w^S = w^R = w^I = 1$ and $w^{k'} = 2$, the overall similarity will range from -2 to 5. For the w_{b_j} formulation as in formula 3.3, we shift r_{xy} to a scale from 0 to 7 and then normalized it to a range from 0 to 1. The underlying principle is that user of opposite similarity should not introduce an "opposite" effect on rating, but rather to have a minimizing effect on the score.

3.5 News Article Scoring

For each daily fetched article, its score consists of the components: the user profile, the user feedback and also the feedback from similar users.

$$Score = w_{profile} \times Score_{profile} + w_{feedback} \times Score_{feedback} \tag{3.9}$$

The weight for profile, $w_{profile}$ and the weight for feedback, $w_{feedback}$, are assumed to be equal to 0.5, i.e. in the mid-point of the scale in the user interface. User can alter this weight by moving along the scale from 0 to 1, so as to put a higher weight on either the profile or the feedback for retrieving the news. (For user interface, please refer to section 3.6.1). $Score_{profile}$ is the normalized user profile score, with the summation of all newly fetched articles' $Score_{profile}$ as the normalization factor. Similarly, $Score_{feedback}$ is the normalized semantic relevance score, with the summation of all newly fetched articles' $Score_{feedback}$ as the normalization factor.

The score for the newly fetched article i as computed in formula 3.9, is then normalized to a final score, $FScore_i$ as follow:

$$FScore_i = \frac{Score_i - Score_{low}}{Score_{high} - Score_{low}} \times 100 \quad (3.10)$$

where $Score_{high}$ and $Score_{low}$ are the scores of highest and lowest scored articles as computed using formula 3.9 respectively. The infomediaries will then rank the daily fetched news articles based on the final scores of news articles as computed using formula 3.10 and present them to users in descending order of their score values.

3.6 User Interface of Collaborative Infomediary

We will provide details in this section about how a user interacts with the Collaborative Infomediary.

3.6.1 User Registration and Preference Setting

First-time users are required to register with Collaborative Infomediary. Every user has his own account for login. They have to set up their user profiles to indicate their preferences during the first login. First, they choose 編輯(Edit) from the menu bar and under this option, click on 個人設定(Preference) to modify the personal setting. There are seven areas for the preference setting as depicted in Fig. 3.2.

Figure 3.2: Seven areas of Preferences setting

Retrieval Settings

The first panel for the preference setting is **檢索設定(Retrieval Settings)**. User has to adjust the relative weighting between user profile and semantic measurement for the news retrieval as shown in Fig. 3.3.

Figure 3.3: Window for weight adjustment on user profile and semantic measurement

Sources of News

User can then adjust his own weighting on the six different newspapers through the second panel – **報章(Sources of Newspaper Articles)** (Fig. 3.4).

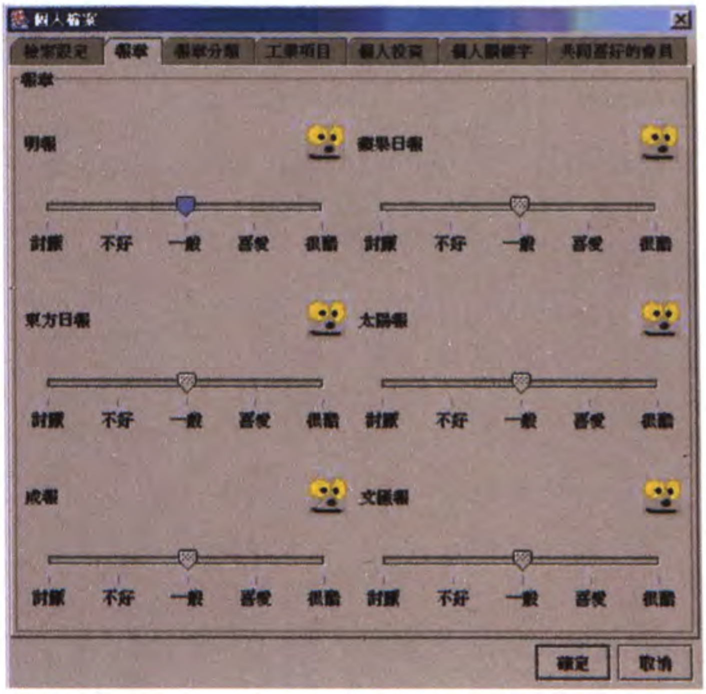

Figure 3.4: Preferences on sources of news articles

News Regions

After that, he can indicate his preference on the three regions of news through the third panel - **報章分類(News Region)** (Fig. 3.5).

Industry

The fourth panel is **工業項目(Industry Item)** (Fig. 3.6). User can select the industry he likes out of the seven industries.

Listed Companies

Then, user proceeds to the fifth panel - **個人投資(Personal Investment)** (Fig. 3.7), in which there is a list of company names and their corresponding

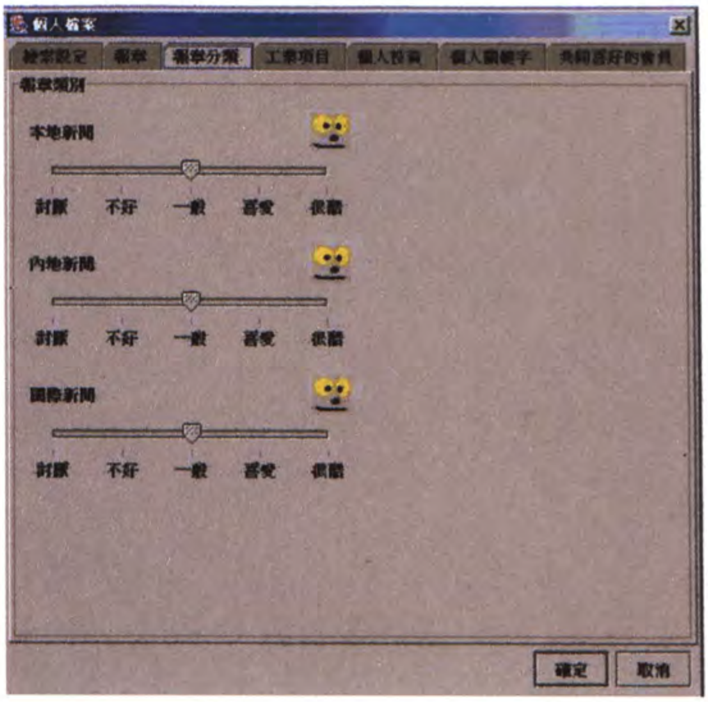

Figure 3.5: Preferences on news regions

stock codes in the Hong Kong Stock Market, for the user to select.

Keywords

User can also enter and edit their specified keywords for news retrieval. This is done in the sixth panel of preference settings – **個人關鍵字(Personal Keyword)** (Fig 3.8). The names of the listed companies which user have selected in fifth panel are also shown in the keywords box.

Collaborative users

The last preference setting – **共同喜好的會員(Collaborative Users)** is a window through which user adjust his own weighting on four domains

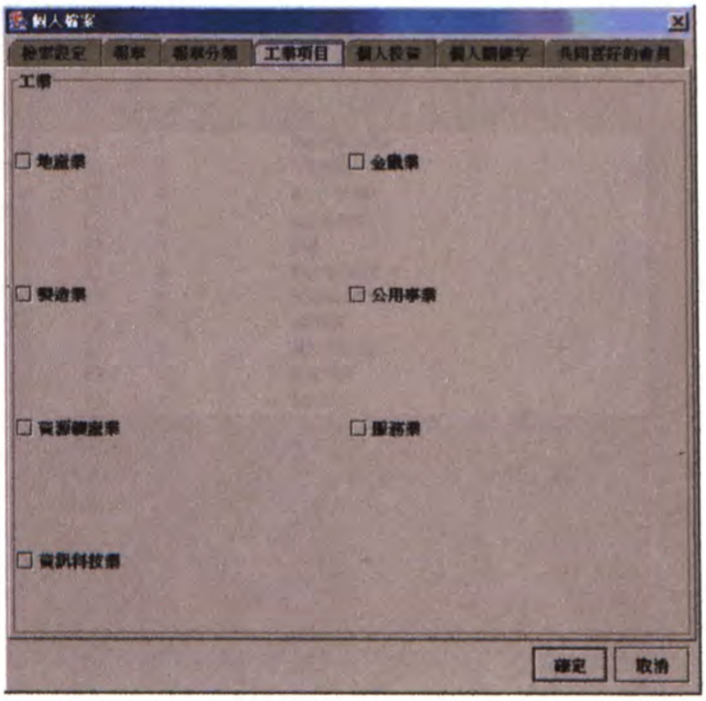

Figure 3.6: Preferences on industries

including: source (報章), news category (報章分類), industry (工業項目) and keyword (關鍵字) for user similarity comparison. (Fig 3.9).

3.6.2 Current Day News Retrieval

Manual / Auto Selection of Collaborative Users

After user has setup his own user profile, i.e. his preference settings, he can choose the **檢視(View)** option in the menu bar and then select from the drop down menu **今日新聞(Today News)**, to view today news articles (Fig 3.10). The Collaborative infomediary utilizes not only the active user own profile and feedback, but also the feedback from other users to rank news. Hence, users can either select collaborative users on his own (Click on

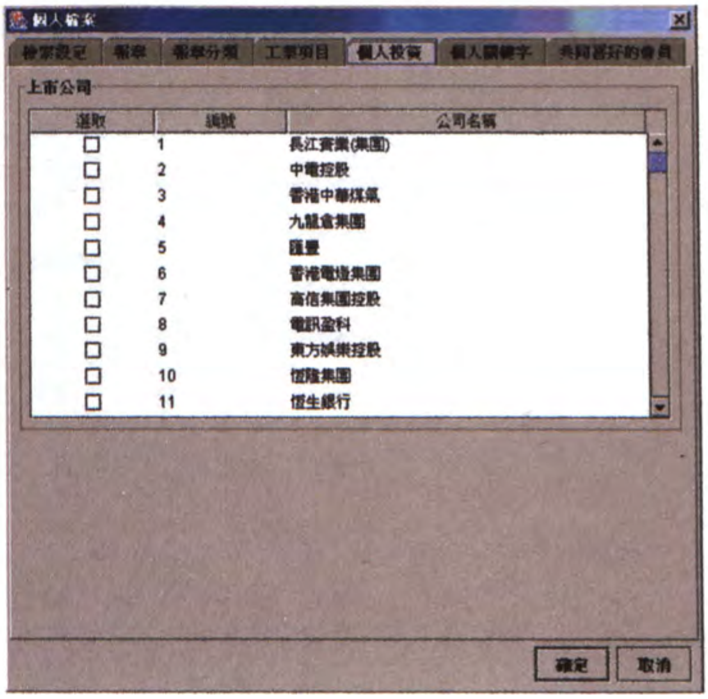

Figure 3.7: Selection on the listed companies

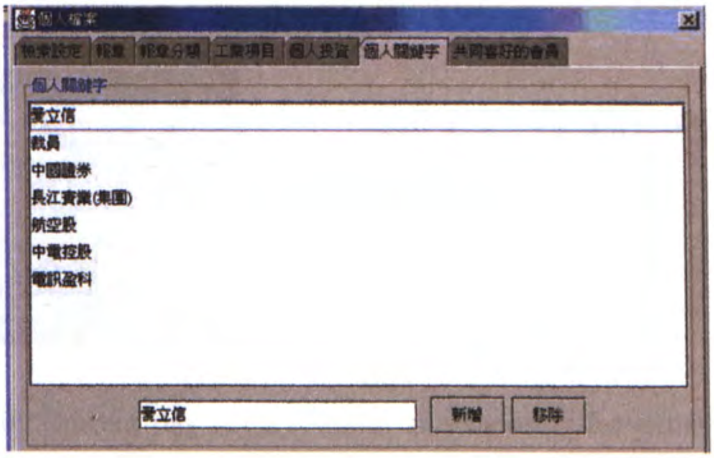

Figure 3.8: Panel for user to enter keywords

自選(Manual)) or let the system choose for him (**自動(Auto)**)(Fig 3.10) .

If "manual" is chosen, a table with the list of other users is displayed for

Figure 3.9: Adjustment for weighting on four domains of user similarity computation

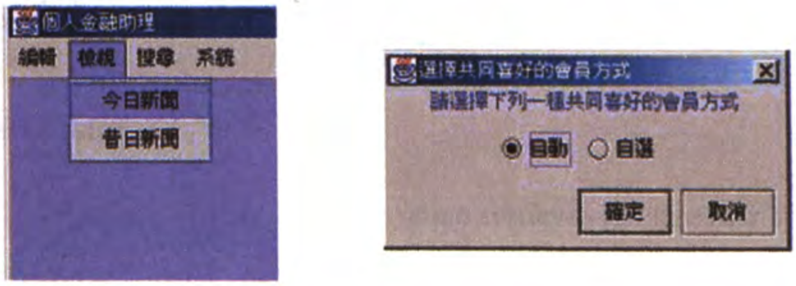

Figure 3.10: Current day news retrieval and choosing for either manual or auto partners selection

the user to choose as 'likeminded users' as shown in Fig. 3.11. The left hand side shows the partners that have been chosen before by users. The symbol '*' indicates that the profile of that partner has been modified since the last time the user has chosen him. The right hand side shows the most relevant partners to the users. Click on the box beside the user name to select the partners. There is a count on the number of users selected by the user at the left bottom corner. No more than ten partners can be selected. The user profiles of the other users can be viewed by pressing 會員資料(User Profile).

Figure 3.11: Manual selection of collaborative partners

News Browsing

After all the preferences are set, the system retrieves the news for the users and the following dialog box prompts out (Fig 3.12). The upper part shows the result of the ranked financial news articles for that current day. The lower part displays the selected article in NewsML format.

Feedback

A dialog box for giving feedback pops out when users choose to read other news articles or close the table. (Fig 3.13)

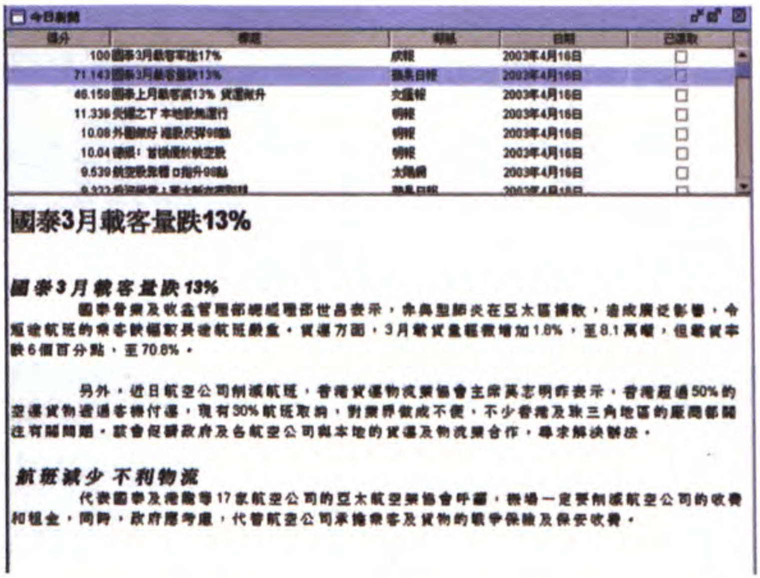

Figure 3.12: Result of ranked financial news on a particular day.

Figure 3.13: User Relevance Feedback Window

3.6.3 Past News Retrieval

User can select 昔日新聞 (Past News) from the option 檢視(View) to search for past news by date (Fig 3.14). And then the search results will be shown as in Fig 3.15.

Figure 3.14: Past news retrieval

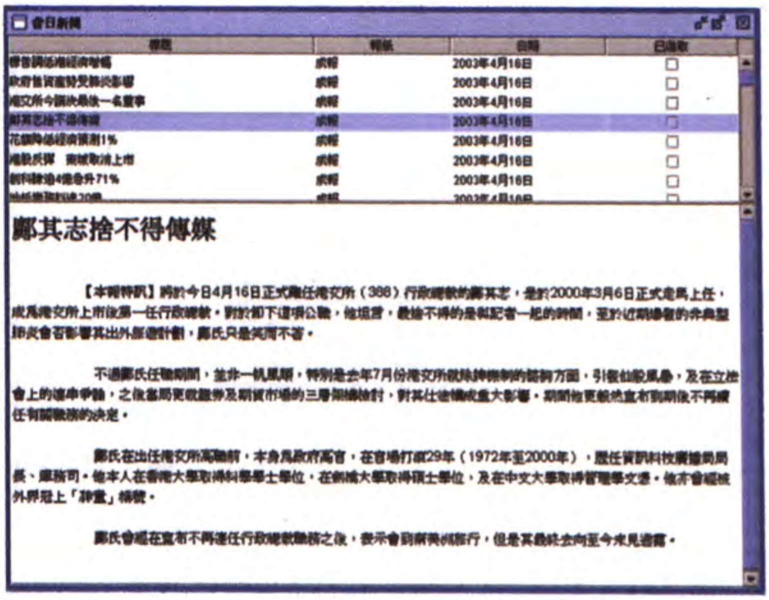

Figure 3.15: Past news browsing.

3.6.4 Search News

If a user wants to search for some specific news articles, he can use the option **搜尋(Search)** in the menu, and then click on **搜尋新聞(Search News)**. Users can specify the date, newspaper source and keywords for the topic of articles (Fig. 3.16). The system returns the following box (Fig. 3.17) if there is no matching document, or the matched result will be shown as in Fig. 3.18. The window is similar to **Today News** except no ranking is provided. Users can also give feedback after reading the articles.

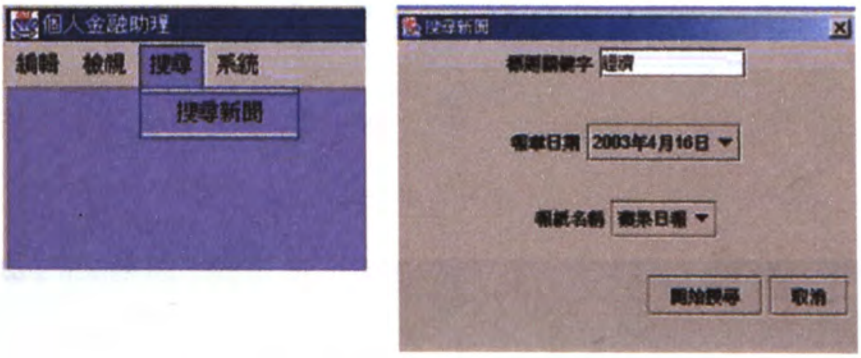

Figure 3.16: Option for user to search news

Figure 3.17: Dialog box if no matching result for the news search

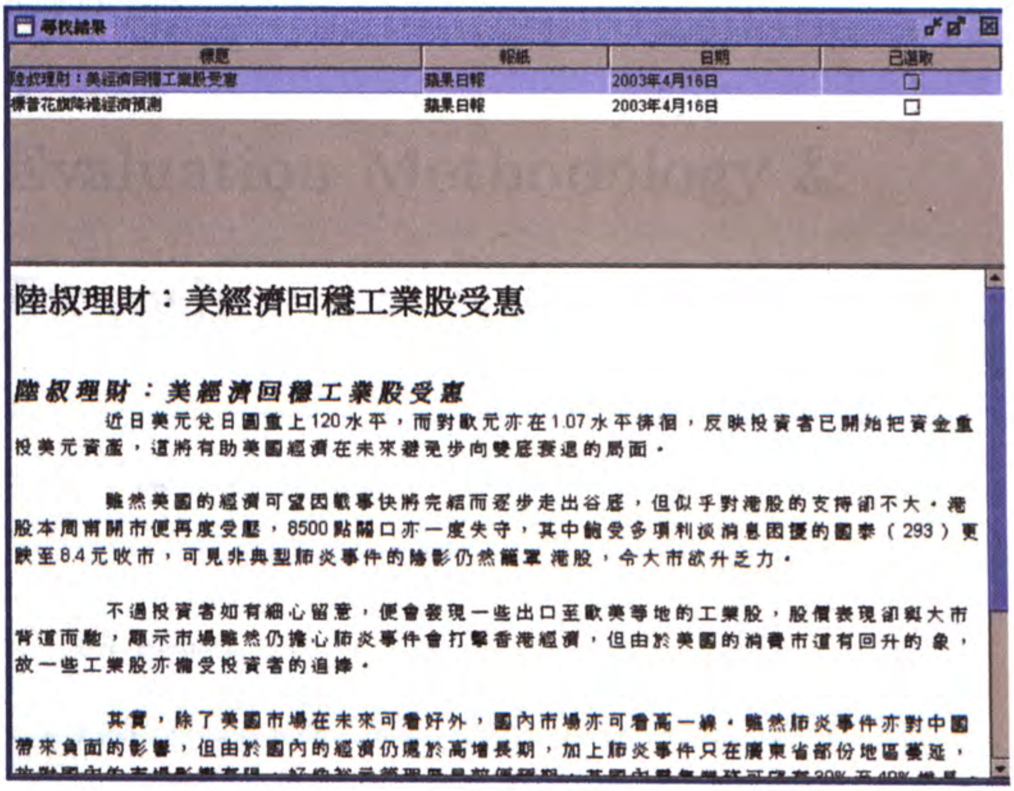

Figure 3.18: Result of news search

Chapter 4

Evaluation Methodology & Experimental Results

We have conducted an experiment, with three main objectives:

1. Find out whether the collaborative component improves the system performance
2. Find out the performance of system under different user similarity thresholds for classifying neighbours
3. Perform an analysis of user similarity threshold against the average number of collaborators

The first objective is the critical issue we are concerning. We would like to know whether the new add-in, the collaborative feature does improve the system performance. For the second and third objectives, they are related to the neighbourhood size to be used in the collaborative feature. The size of neighbourhood and the similarity magnitude between the users, have significant impact on the recommendation quality. In order to determine the effect of neighbourhood size and similarity magnitude, we vary the size of neighbourhood by setting a similarity threshold. We would like to find out the critical point at which the improvement gains diminish.

4.1 Experimental Design & Setup

In order to study the effect of collaborative feedback on Collaborative Infomediary, an experiment was conducted. The experiment is a user evaluation involving 10 subjects from the Chinese University of Hong Kong. All of them are graduate students majoring in Systems Engineering and Engineering Management Department.

Before the experiment commenced, subjects were given a briefing on the purpose of the experiment. They were told that the purpose of the experiment is to evaluate the system performance of the "Collaborative" feature of the Personal Financial Infomediary, which is an intelligent agent that helps users to search for Chinese financial news post on web. Their task is to set up a user profile representing their interests and then provide feedback on the news articles they read. A 20 minutes tutorial session was conducted to let subjects acquire the general understanding about the functionalities: (1) user login and logout, (2) user profile configuration, (2) news browsing, and (4) providing feedback; and user interface of the system. During the tutorial session, a tutorial guide (Appendix E) was distributed to the subjects. We went through the tutorial guide page by page with the subjects in order for them to be familiarized with the system. A clear explanation were given on how to set up the user profile and what each tag in the user profile interface represented.

Approximately, 170 to 220 news articles from six sources of newspapers are fetched everyday. There are six setups for each subject. Each setup corresponds to different similarity thresholds set. We have 6 different user similarity thresholds: 0.3, 0.4, 0.5, 0.6, 0.8 and 1. Under each setup, 30 top ranked news articles are returned on each day based on the user profiles, user feedback and feedback from neighbours on the previous days. To be qualified as neighbours, the user similarity with the target subject, i.e. w_{peer}, should be larger than the thresholds set. All of the news articles returned from the 6 setups are gathered and presented to the subject. The experiment proceeded to next day only after all subjects had finished browsing and giving feedback on the news articles on the current day. A batch job was then run between days to find out the collaborative users for the subjects.

The task of each subject is to set up his own user profile, which represents his interests, and to provide feedback on his own rankings and ratings of the news articles presented to him. The subjects use the system for five consecutive days. During each day, all the news articles returned from the 6 setups are presented to the subjects. However, subjects have no knowledge on the setup source of the news articles, i.e. they do not know the news articles they read are from which similarity threshold setup. The purpose of this design is to avoid subject bias. Each subject is required to give his/her feedback for each news articles both on a rating basis (0-100) with 50 as the neutral point, and also he/she needs to rank the articles in the order of relevancy with 1 being the most relevant. Subjects were reminded about these feedback rules. They were also reminded not to move the domain weighting sliders for system selection of collaborators, and also the weighting adjustment for user profile and semantic measurement for news retrieval, so as to preclude the effect on performance due to these variables. In order to avoid confusion, several functionalities in the original system has also been disabled in experiment setup: manual selection of collaborators (section 3.6.2), past news retrieval (section 3.6.3), and search news articles (section 3.6.4).

4.1.1 Performance Measures

In the experiment, we employed the performance measures precision and recall rates to measure the effectiveness of the system performance. F-measure, a well-accepted single measure that tries to balance precision and recall was also used in our evaluation [55].

Precision and recall

The standard precision, recall measures are on basis of absolute relevance judgments. They require a two level relevance judgment, i.e. relevant and non-relevant. The set of news articles, according to the results of recommender system, is divided into two subsets, the retrieved subset and non-retrieved subset. The precision and recall measures are expressed by:

$$Precision(percentage\ of\ retrieved\ news\ articles\ that\ are\ relevant)$$
$$= \frac{number\ of\ retrieved\ news\ articles\ that\ is\ relevant}{total\ number\ of\ retrieved\ news}$$

$$Recall(percentage\ of\ relevant\ items\ that\ were\ returned)$$
$$= \frac{number\ of\ relevant\ news\ articles\ retrieved}{total\ number\ of\ relevant\ news}$$

F-measure

We also employed the F-measure as our evaluation. It is calculated as follow:

$$F - measure = \frac{(2 \times recall \times precision)}{(recall + precision)}$$

Here, we take the number of news articles retrieved by the system with system score over 50 as the total number of retrieved news articles. Also, news articles where user ratings of over 50 are taken as relevant while those under 50 as non-relevant. Hence, the total number of relevant news is the number of news articles user rated over 50.

4.2 Experiment Results & Discussions

4.2.1 Similarity Threshold against average number of collaborators

As shown in table 4.1, we found out that nearly all the other users in the experiment are included as neighbours when we set the threshold cutting to 0.3. On moving the threshold to 0.4, only half of the users are included. Only a few subjects have collaborators with similarity over 0.5. There are no collaborators with similarity over 0.6.

Similarity Threshold	Average number of Collaborators
0.3	8.80
0.4	4.80
0.5	0.40
0.6	0.00
0.8	0.00
1	0.00

Table 4.1: Similarity threshold against average number of collaborators

4.2.2 Performance Measures among setups

From the log files record by the system, we found out that one subject, gave extremely low ratings to the news articles (under 10). This subject has a user profile with over 10 keywords that are financially irrelevant. Her data are excluded from the analysis. Another subject, who has a fluctuating results is also omitted in the analysis. The performance measures for the other 8 subjects are then studied. Also, since all the three setups of similarity threshold 0.6, 0.8 and 1 correspond to no collaborators, the performances are the same under these 3 setups, the plot of similarity threshold 0.6 setup represents all the three setups.

Precision, recall and F-test

The comparisons of the average precision, recall and F-measure of the 4 setups (with similarity threshold of 0.6 represent all the three setups of similarity threshold 0.6, 0.8 and 1.0) on each day are also presented in Fig B.1 to Fig B.3 respectively. Table 4.2, 4.3 and 4.4 depict the average and standard deviation of precision, recall and F-measure for 4 setups respectively.

Similarity threshold value of setups	day 0 Mean	day 0 Standard deviation	day 1 Mean	day 1 Standard deviation	day 2 Mean	day 2 Standard deviation
0.3	0.6782	0.4275	0.5578	0.2502	0.5787	0.2353
0.4	0.6782	0.4275	0.5516	0.2438	0.5913	0.2265
0.5	0.6782	0.4275	0.5766	0.2217	0.6013	0.2350
0.6	0.6782	0.4275	0.6378	0.1982	0.5587	0.2441

Similarity threshold value of setups	day 3 Mean	day 3 Standard deviation	day 4 Mean	day 4 Standard deviation
0.3	0.5986	0.1829	0.5973	0.1386
0.4	0.6130	0.1828	0.6031	0.1410
0.5	0.7103	0.1830	0.6444	0.1680
0.6	0.6955	0.2099	0.6180	0.1503

Table 4.2: Average and standard deviation of precision rates for 4 setups on 5 consecutive days

The results show that with collaborators' feedback (correspond to the setups of similarity threshold of 0.3, 0.4 and 0.5) obtains the best performance. From the plot of F-measure, under similarity thresholds of 0.3, 0.4 and 0.5 which correspond to collaborative feedback incorporated, the F-test improves sharply from day 0 to day 1, then increase slightly or keep constant from day 1 to day 2, rise up sharply again from day 2 to day 3 and then drops from day 3 to day 4. The performance of collaborative feedback improves daily except during day 4. However, for the setups with no collaborators, the F-test fluctuates. F-measure increases slightly from day 0 to day 1 and

Similarity threshold value of setups	day 0		day 1		day 2	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
0.3	0.5464	0.3713	0.9054	0.2003	0.8491	0.1864
0.4	0.5464	0.3713	0.8911	0.2017	0.8405	0.1812
0.5	0.5464	0.3713	0.6624	0.2349	0.6313	0.3017
0.6	0.5464	0.3713	0.4413	0.1728	0.3775	0.3058

Similarity threshold value of setups	day 3		day 4		
	Mean	Standard deviation	Mean	Standard deviation	
0.3	0.8326	0.1709	0.7268	0.2071	
0.4	0.8052	0.2024	0.7150	0.2077	
0.5	0.6841	0.2794	0.5960	0.1344	
0.6	0.5300	0.2070	0.4760	0.2922	

Table 4.3: Average and standard deviation of recall rates for 4 setups on 5 consecutive days

Similarity threshold value of setups	day 0 Mean	day 0 Standard deviation	day 1 Mean	day 1 Standard deviation	day 2 Mean	day 2 Standard deviation	day 3 Mean	day 3 Standard deviation	day 4 Mean	day 4 Standard deviation
0.3	0.4860	0.3351	0.6526	0.2122	0.6658	0.1902	0.6916	0.1717	0.6120	0.1961
0.4	0.4860	0.3351	0.6428	0.2022	0.6787	0.1906	0.6887	0.1777	0.6085	0.1910
0.5	0.4860	0.3351	0.5843	0.1747	0.5819	0.2591	0.6707	0.2091	0.5905	0.2160
0.6	0.4860	0.3351	0.4783	0.1076	0.3872	0.2253	0.5718	0.1341	0.4595	0.2129

Table 4.4: Average and standard deviation of F-measure for 4 setups on 5 consecutive days

sharply from day 2 to day 3, while it drops from day 1 to day 2 and from day 3 to day 4.

We have conducted a two-way analysis of variance (ANOVA) to identify if there are any significant effects of the factors, similarity threshold setups and days, and their interaction. As shown in Table 4.5, the p-values are 0.069, 0.016 and 0.973 for between consecutive days, between similarity thresholds and their interaction respectively. The results highlight that similarity threshold has a significant effect on the performance of the Collaborative Infomediary.

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F-crit*
Between days	0.470491	4	0.117623	2.224823	**0.069356*	2.436317
Between similarity thresholds	0.561297	3	0.187099	**3.539044**	*****0.016405***	2.669256
Interaction	0.230704	12	0.019225	0.363654	0.973905	1.82192
Within	7.401402	140	0.052867			
Total	8.663894	159				

Number of subjects: 8.

* Significant at $p < 0.07$

** Significant at $p < 0.02$

Table 4.5: Two-way ANOVA examining the effects of setups and days ,and their interaction on 5 consecutive days

4.2.3 Performance Measures against Similarity Threshold

Though the number of collaborators decreases with similarity threshold, it would also imply a higher similarity between the collaborators with the subject. These two factors counteract each other. We would like to see at which point the performance of system diminishes and also if the collaborative feedback improves the system performance.

A plot of F-measures for 5 consecutive days are shown in Fig B.4. As from similarity threshold of 0.6 onwards, the setup involves no collaborators; we can classify the region of the plot into collaborative setups and non-collaborative setups with 0.6 as the cutting point. The plot of F-test indicates the collaborative feedback improves the system performance. Also, we can find out that the F-measure drops from a point between the similarity threshold ranges from 0.4 to 0.5 during day 1 to day 4. This indicates that the system performance diminishes at this point. In order to determine if the factor of similarity threshold setup has effect on the performance of the Collaborative Infomediary during each day from day 1 to day 4, we conduct the ANOVA tests for each of the setups in each day. Table 4.6 shows the ANOVA results of each day for all the four setups. The p-values for the fours days are 0.211451, 0.045298, 0.48451 and 0.401921 respectively. There is significance difference in the performance on day 2 between the similarity setups.

To better understand the significance of improvement between consecutive similarity threshold setups, we employed Paired T-test to assess whether the means of F-measures of two adjacent similarity thresholds are *statistically* different from each other. Table 4.7 shows the p-values of t-test and the computation of the p-values can be found in Fig. B.5 and B.6. From the Table 4.7, p-value from the t-test between similarity threshold setups of 0.3 and 0.4 is not significant for individual days from day 1 to day 4, and also for

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F-crit*
Day 1						
Between setups	0.153723	3	0.051241	1.60086	0.211451	2.946685
Within setups	0.896233	28	0.032008			
Day 2						
Between setups	0.434389	3	0.144796	3.041981	* *0.045298*	2.946685
Within setups	1.332782	28	0.047599			
Day 3						
Between setups	0.077165	3	0.025722	0.837946	0.48451	2.946685
Within setups	0.859489	28	0.030696			
Day 4						
Between setups	0.126726	3	0.042242	1.012457	0.401921	2.946685
Within setups	1.168219	28	0.041722			

* Significant at $p < 0.05$

Table 4.6: Two-way ANOVA examining the effects of four setups in 4 consecutive days.

an aggregate of all four days. Based on these observations, on increasing the similarity thresholds from 0.3 to 0.4, the higher similarity of users counteract with the decreased numbers of collaborators, and thus, the performance of Infomediary is not significantly affected. The p-value results for t-test between similarity threshold setups of 0.4 and 0.5 show that there is no significant difference between the two setups for each individual day. However, the difference between these two setups of all four days is significant at the significant level of 0.07. In this case, we observe that the drop of the number of collaborators from 4.8 to 0.4 on moving from similarity threshold from 0.4 to 0.5 did affect the performance of the system significantly. Similarly, for the comparison between the similarity setups of 0.5 and 0.6, p-values results for t-test in day 2 and day 3 suggests there is significant difference at significant level of 0.07. Also, the F-measure performance between these two setups is significantly different, on the four days as a whole. The results imply that with collaborative feedback i.e. similarity threshold setups of 0.5, the Infomediary performance did improve on day 2 and day 3 and on the four days as a whole, significantly as compared to the setups with no collaborators, i.e. similarity threshold setup of 0.6. From the ANOVA and t-test, it shows that the collaborative feedback improves the retrieval performance of Collaborative Infomediary significantly.

Threshold Values of setups	Between 0.3 and 0.4	Between 0.4 & 0.5	Between 0.5 & 0.6
Day 1	0.224811	0.260452	0.213054
Day 2	0.411198	0.233195	**0.067496*
Day 3	0.822103	0.703591	**0.067843*
Day 4	0.484183	0.501534	0.198149
All 4 days	0.873898	**0.065454*	***0.00145*

* Significant at $p < 0.07$

** Significant at $p < 0.005$

Table 4.7: p-value: T-test for Means between adjacent setups

Chapter 5

Related work on the Measuring Factors that Influence the Success of Infomediary

5.1 Different approaches to IS success measurement

Many practitioners are facing the need to evaluate whether the information system implementation is successful or effective. The subject of information system (IS) success or effectiveness has been widely reviewed in the IS literature and its importance has been emphasized. According to a review of over 50 end-user information system satisfaction (EUISS) papers conducted by Au et al. [2], there are three approaches of system success measures. They are cost-benefit analysis, system usage and end-user satisfaction measurement.

Cost-benefit analysis is the most objective measurement. The net value of the information system to the organization is the difference between the actual benefits in terms of improved organizational effectiveness, and the cost of information development. This approach, however, suffers from a number of weaknesses. First, it is difficult to show causality, i.e. if the particular benefit is directly or solely due to the new information system. Secondly, the costs and benefits are sometimes intangible and therefore difficult to compute the monetary value. Thirdly, these objective data may not be recorded and so, not available.

System usage has also been suggested as another measure of IS success. This approach reflects the degree of confidence users have in the effectiveness of their information systems. For instance, the amount of user connect time. However, some critics argued that the use of IS, either actual or perceived, is only relevant when it is voluntary but not as a mandatory requirement.

End-user satisfaction has been the most frequently used measure for evaluation of information system (IS). According to Au et al. [2], it has a high degree of face validity due to reliable instruments being developed by past researchers, and also as most other measures are either conceptually weak or empirically difficult to validate. User satisfaction is a critical construct for it is a surrogate of management information systems (MIS) effectiveness, and also of its relation to other important variables in system design and analysis. There are a number of literature in support of using satisfaction as the critical criterion for measuring IS success. Nolan and Seward [47] argued that user satisfaction is the most important criterion in measuring IS success and failure. Later as asserted in Ives et al. [32] user information satisfaction (UIS) is a perceptual or subjective measure of system success; it serves as a substitute for objective determinants of information system effectiveness which are frequently not available. UIS also measures how users view their information system rather than the technical quality of the system. A "good" information system perceived by its users as a "poor" system is a poor system. It is the main argument for making user satisfaction as a suitable candidate of IS success assessment.

In a past research study, Delone and McLean [23] reviewed 100 papers containing empirical IS success measures that had been published in seven publications during the seven years 1981-1987. In the paper, they classified the huge range of IS success measures they found into six categories. They are: 1.information quality, 2.system quality, 3. use, 4. user satisfaction, 5. individual impact, and 6. organizational impact. It can be seen that *user satisfaction* has been one of the dimensions for IS success evaluation. Besides, Rivard and Huff [56] have also linked the success of end user computing as overall user satisfaction.

5.2 User Information Satisfaction/End-User Computing Satisfaction

5.2.1 Definition of user satisfaction

What is User Satisfaction? The dictionary defines *satisfaction* as fulfillment of a need or want. What exactly is it? There are lot of literatures trying to give a definition to it. As mentioned by Tessier et al. [68], *satisfaction* is clearly a state of mind experienced (or not experienced) by the user. User's satisfaction will be a function of how well the product fits his requirement. As for IS end-users, Ives et al. [32] defined *user information satisfaction* (UIS) as the extent to which users believe the information system available to them meets their information requirements. It is a set of user's beliefs about the relative value of the IS. Doll and Torkzadeh [24] defined *end-user computing satisfaction*(EUCS) as the affective attitude towards a specific computer application by someone who interacts with the application directly. It is the IS end-user's overall affective evaluation of the pleasurable level of consumption-related fulfilment experienced with the IS. IS end users refer to non-technical personnel who use or interact with the system directly, as opposed to technical personnel who design the IS.

5.2.2 Factors/dimensions affecting IS user satisfaction

According to Au et al. [2], the most frequently used instrument for EUS is developed by Bailey and Pearson [4], who identified a list of 39 indicators that contribute to end user satisfaction (EUS) with IS. The instrument is then re-evaluated by Ives et al. [32], and later again by Baroudi and Orlikowski [6], which result in a shortened (comprising 13 items) measurement, which can be broadly grouped into three main dimensions: **Information Quality**, **EDP Staff and Services**, and **User Knowledge**. Typical measures of **Information Quality** includes accuracy, relevance, completeness, currency, timeliness, format, security, documentation and reliability. Measures of **EDP Staff and Services** mainly comprise staff attitude, relationships, level of support, training, ease of access and communication. Finally, measures of **User Knowledge** mainly include user training, user understanding and participation.

Doll and Torkzadeh [24] identified five factors for measuring EUS: **content, accuracy, format, ease of use** and **timeliness**. These factors are mainly related to Information Quality mentioned above. Other dimensions such as **Top management support**, **Organization support** or user support structures of any kind are also suggested as influencing IS user satisfaction [44]. In addition, two other IS dimensions, namely **System Quality** and **Interface Quality** are categorized by other researchers from the IS attributes list [65]. Most measures in the former dimension are engineering-oriented technical performances such as speed, features, etc. The latter category refers to the interaction between the end-user and the computer system.

After the review of over 50 papers, Au et al. [2] concludes that the major dimensions of IS performance relevant to and having a significant impact on EUS consists of **Information Quality**, **System Quality** and **System Support Services**. With reference to previous validated instruments [24, 32], the **Information Quality** construct is measured by nine indicators, namely accuracy, availability, reliability, updatedness, relevance, timeliness, completeness, presentation format and accessibility. Six indicators, namely, response time, reliability, functionality, flexibility, user friendliness and ease of integration, are used to measure the **System Quality** construct. Finally, the **System support service** will be measured by another six indicators, namely, promptness, reliability, responsiveness, technical competence, attitude of system support people, ability of keeping accurate records and provision of training course. In general, most of these studies have used a multivariate approach when measuring satisfaction and then tended to operationalize satisfaction from a list of indicators, and inferred a level of satisfaction from the sum of responses to these indicators [11].

5.3 Evaluation of Web-site

As discussed in the chapter of introduction before, the World Wide Web has become a major information dissemination channel. Hence, Internet has provides a supportive context for effective information seeking by information users [11]. So, it is in some sense related to information system, or a network or a hybrid of traditional information system, as user tries to seek information from the Internet. Though there are massive literatures proposing evaluation measures on traditional information system, like end user information system satisfaction (EUISS) discussed in previous section, according to Bruce [11], an attempt to find out how satisfied users are when they look for information using the network is overdue. In [11], Bruce defined information seeking on the internet as a purposeful interaction with an Internet information resource or resources aimed at obtaining information to inform, treat, or resolve a problem. In this study, the author aimed to find out how satisfied end-users are when they search for information using the Internet. However, the factors contributed to "satisfaction" was not studied. It is only a single-item scale, hence it did not provide sufficient content domain sampling of complex constructs. It is generally believed to be unreliable, since it does not allow internal consistency to be calculated [48]. Furthermore, single-item measures provide no details for interpretation of the exact meaning of satisfaction. Later in [62], Spink proposed to evaluate a web search engine from a user-centered approach, which includes *effectiveness* and *usability*. Evaluation on *effectiveness* focus on measuring the impact of users' interactions on their information problem and their moves through the different stages of their information seeking process. Pre-search questionnaire and post-search questionnaire was used to capture the state of user, providing measurement of changes by users resulting from their interaction with the search engine. *Usability* evaluation includes 8 criteria on screen layout and system capabilities for users. The evaluation measures are built on extension of various literature. However, the author have not tested the validity of those measures.

5.4 Web Customer Satisfaction

Other than serving as information dissemination channel, the Internet also provides a mean for users to shop online. As from previous sections, there are different established models to measure user information satisfaction (UIS) and end-user computing satisfaction (EUCS). These models are perceived as inappropriate for measuring customer information satisfaction in electronic commerce. Wang et al. [72] argued that these models are targeted for conventional data processing or end-user computing environment. They are not appropriate for the digital marketing context. UIS and EUCS instruments focus primarily on general or specific user information satisfaction within an organization rather than on customer satisfaction with regard to web site.

They have not been developed and validated for measuring web customer information satisfaction.

5.4.1 Customer satisfaction

The authors in [25] proposed a definitional framework for consumer satisfaction for resolving inconsistencies of consumer satisfaction. In the study, three components of consumer satisfaction has been identified: 1. summary affective response which varies in intensity, 2. satisfaction focus around product choice, purchase and consumption and 3. time of determination which varies by situation, but is generally limited in duration. Summary affective response is defined as the holistic nature of consumer's state of satisfaction by Giese and Cote [25]. The focus is the object(s) of consumer's state, and timing refers to the temporal existence of satisfaction. Giese and Cote [25] provided a framework for other research study which includes context specific definition of consumer satisfaction. Kotler [41] viewed satisfaction as the consequence of the customer's experiences during various purchasing stages: need arousal, information search, alternatives evaluation, purchase decision and post-purchase behaviour. The authors in [63] have identified information satisfaction and attribute satisfaction as antecedents of satisfaction. Information satisfaction is based on the quality of the information used in deciding to purchase a product, whereas attribute satisfaction measures the consumer's level of contentment with a product [63](p.17).

5.4.2 Factors/Dimensions affecting customer information satisfaction

Due to the lack of instrument in measuring customer information satisfaction (CIS) on web sites, Wang et al. [72] developed a multidimensional instrument to measure customer information satisfaction (CIS) for web sites that market digital products and services. In the study, the authors employed the definition proposed by Giese and Cote [25]. Customer information satisfaction (CIS) for digital marketing is conceptualized as "a summary affective response of varying intensity that follows consumption, and is stimulated by focal aspects of sales activities, information systems (websites), digital products/services, customer support, after-sales service, and company culture." In the study, four aspects of customer information satisfaction distinguish it from traditional marketing: **information**, **information processing**, **IS content** and **IS interface**. **Information** refers to the information product transmitted via Internet, for example, books, online newspaper; **Information processing** is the digital services processed over Internet like online banking and security transactions; and **IS content** and **IS interface** refers to the content and interface of the web-based information systems (websites). The authors also argued that conventional UIS and EUCS instruments appear to omit several important marketing aspects underlying the CIS construct, such as digital products, sales activities, customer support, etc. Hence, the authors reviewed an extensive list of literature on user information satisfaction, end-user computing satisfaction, and traditional customer satisfaction to obtain 36 items for an initial item pool for CIS scale, with 5 more items generated from surveys and interviews. After rigorous statistical validation procedures (e.g. exploratory factor analysis), 7 dimensions with 21 items of CIS are identified. The dimensions are: **ease of use**, **information content**, **innovation**, **security**, **customer support**, **digital product/services**, and **transaction and payment**. The comparison of the dimensions between UIS, EUCS, and CIS are given in the following table 5.1.

UIS	EUCS	CIS
Knowledge and Involvement		
EDP Staff and Service		
	Ease of Use	Ease of Use
Information Product	Format	
	Content	Information Content
	Accuracy	
	Timeliness	Innovation
		Security
		Customer Support
		Digital Products/Services
		Transaction and Payment

Table 5.1: Comparison of Underlying Dimensions Between UIS, EUCS, and CIS

Based on the definition of customer satisfaction by Kotler [41], McKinney et al. [45] proposed that web customer satisfaction is formed at the information search stage and attempted to identify the construct for this defined web customer satisfaction. In the study, the authors synthesized the instrument from the perspectives suggested by Spreng et al. [63]. Hence, the construct is broken up into two major dimensions: Information quality (IQ) and System quality (SQ). The authors quoted from various literature [66, 33] that aspects with product information (related to IQ) and web site designs (related to SQ) are both important determinants in offering customer satisfaction. In online shopping, the experience of using a Web site during the information search phase could then be affected by IQ and SQ. Web site has long been assumed a critical role for information delivery and that the quality of information is considered critical too. And as it is feasible to separate content from the content delivery system in web site, the authors suggested the approach to model information and system aspects separately for web customer satisfaction. In the study, six factors for information quality and system quality are identified respectively. They are **understandability**, **reliability**, **usefulness**, **relevance**, **adequacy** and **scope** in the information quality aspects; **access**, **usability**, **navigation**, **entertainment**, **hyperlinks**, and **interactivity** in the system quality domain. Lee et al. [42] has developed a methodology called AIM quality that provided a pragmatic basis for IQ assessments and benchmarks. The authors performed a review of literature and grouped the IQ dimensions into four IQ categories: intrinsic IQ, contextual IQ, representational IQ, and accessibility IQ. Intrinsic IQ implies that information has quality in its own right. Contextual IQ highlights the requirement that IQ must be considered within the context of the task at hand; it must be relevant, timely, complete, and appropriate in terms of amount, so as to add values. Representational and accessibility IQ emphasize the importance of computer systems that store and provide access to information; i.e. the system must present information in such a way that it is interpretable, easy to understand, easy to manipulate, and is represented concisely and consistently; also the system must be accessible but secure. The model developed is of four quadrants, depending on whether information is considered to be a product or service, and on whether the improvements can be assessed against a formal specification or customer expectation. When it is assessed so as to meet or exceed consumer expectation, it can be classified into useful information or usable information, if information serves as a product or service respectively. As useful information, the IQ dimensions are **appropriate amount**, **relevancy**, **understandability**, **interpretability** and **objectivity**. If it is classified as usable information, the IQ dimensions are **believability**, **accessibility**, **ease of operation**, and **reputation**.

In a study published in *Management Science,* Keeney [38] proposed to evaluate the success of Internet Commerce from customer perspectives. He proposed to model the problem as a "value focused thinking" process and he interviewed over one hundred individuals about their values in using Internet Commerce that they experienced or envisioned. Keeney [38] characterized the "value proposition" concept as the benefits and costs of what the Internet offers customers as compared to currently available traditional means. There are four terminologies defined by Keeney [38] in relation to this "value proposition approach". The *decision context* presents the alternatives appropriate for a given decision situation; *values* are the principles used for evaluating the desirability of possible alternatives, *fundamental objectives* are the ends objectives and *means objectives* are the methods to achieve the ends.

Keeney [38] used the concepts of value focused thinking in three steps. First, a list of customer values is developed through personal interviews. In the second step, the values identified in the first step are converted into objectives. An objective is defined as something one wants to strive towards and is composed of three features, decision context, an object and a direction of preference. At the third stage, values were organized so as to indicate their relationships. Similar objectives are classified into categories. As a consequence, the 91 objectives identified are grouped into 25 categories. Out of these 25 objectives, 9 constructs is classified under *fundamental objective* - one of the fundamental reasons for purchasing on the Internet or not (i.e. objective customer considers as important for Internet Commerce). The other 16 constructs are under *means objective*, which helps to achieve one of more of the other objectives (i.e. objective that influence online purchase). The relationships among the fundamental and means objectives are presented in a means-ends network.

It employed value proposition that is operationalized through the value-focused thinking approach. Based on the interview of over one-hundred individuals about the pros and cons of using Internet commerce, a result of twenty five objectives that were influenced by Internet purchases were obtained. The objectives were separated into means and fundamental objectives. Fundamental objectives make explicit the values that one cares about and define the consequences of concern. On the other hand, means objectives are the methods to achieve the ends. The ultimate fundamental question, i.e. overall objective is considered as to maximize customer satisfaction.

Based on the work of Keeney [38], Torkzadeh and Dhillon [69] did a study and gathered data to develop measures of constructs suggested by Keeney in his study. The instrument is 5-factor, 21-item that measures means objectives in terms of *Internet product choice*, *online payment*, *Internet vendor trust*, *shopping travel*, and *Internet shipping errors*; 4-factor, 16-item that measures fundamental objectives in terms of *Internet shopping convenience*, *Internet ecology*, *Internet customer relation*, and *Internet product value*. The instruments were tested for purification, unidimensionality, reliability, brevity and simplicity.

Chapter 6

Research Methodology

6.1 Methodological Approach

In our study, we attempt to understand what customers value most in using Infomediary. We are going to develop an instrument of measuring factors that influence the success of Infomediary. And there are three possible contexts for measurement development. In situations where there is a strong theory, items of contract are generated using established theory base. In other cases where there is a weak theory, it is prudent to augment theory with practice and use a combination of theory and practice for item generation. Where there is no theory, researchers can rely on experienced professionals for item generation. Since there is no widely accepted definition of Infomediary satisfaction construct, we generated a list of items based on Keeney [38]. Keeney [38] provided us a structured foundation to evaluate the success of Internet commerce. However, the values proposed in Keeney [38] may not be specific enough for evaluating Infomediary. Infomediary provides a platform for both the large and rapidly growing consumer base and supplier base to meet and match their needs. It helps to facilitate the consummation of transaction. Hence, Infomediary acts as mediator of information and transaction, with its function rests primarily on solving the information aspect problem. In order to develop an instrument for evaluating the success factors of Infomediary, we would adopt the "value proposition approach" suggested by Keeney [38] as the building block for instrument in our research. And then we try to hypothesize a more comprehensive list of factors a priori, on top of the means objectives and fundamental objectives identified in Keeney [38], by addition of dimensions identified through the review of other related MIS literature. We then intentionally write items to tap each dimension. After the list of values are generated, we build a network to shows the organization of the customer values in using Infomediary aspect. Then we would like to validate list of items identified. We perform psychometric analysis to purify, test and validate a set of items for the recommended instrument for Infomediary.

6.2 Construct Definition and Item Pool Generation

6.2.1 Customer Values on Infomediary

First, our understanding of the value of Infomediary was based on the concept of "value propositions". We characterize the value proposition as benefits and costs of what the Infomediary offers to the customer. According to Torkzadeh and Dhillon [69], in value-focused thinking, we need to consider three classes of definition: *decision context*, *values*, and *fundamental objectives*. The decision context presents alternatives appropriate for a given decision situation and is specified by the range of activities being contemplated. Values are principles used for evaluating the desirability of possible alternatives in a specific decision situation. Values come into play prior to a given "decision problem". We would like to define the *decision context* is "whether or not to use Infomediary before making a purchase of product or service", while *values* are the principles used for evaluating the desirability of using Infomediary. Also, in assessing the value of Infomediary to the customer, the ultimate fundamental question is "maximize customer satisfaction". *Fundamental objectives* make explicit the values that one cares about and define the consequences of concern. On the other hand *means objectives* are the methods to achieve the ends. In this case, *means objectives* influence the people usage of Infomediary while *fundamental objectives* are perceived by user to be important for Infomediary. Thus, the measurement of success factors of Infomediary relies heavily on the functions of Infomediary from the point of view of users.

6.2.2 Means Objectives and Fundamental Objectives

In e-commerce, Infomediary functions not only as third party provider of unbiased information but also a business matchmaker. Infomediary is e-commerce company leveraging the Internet to unite buyers and suppliers in a single, efficient virtual marketspace to facilitate the consummation of a transaction [27]. So, the means and fundamental objectives described by Keeney [38] are also applicable to Infomediary, as customer use Infomediary as a tool, to help them in deciding whether to make an Internet purchase. Though the importance of the objectives may change in this case, we still include them into our lists so as not to miss out any objectives customers may take into consideration.

Infomediaries are in the information business. They are competing on their ability to capture and manipulate information in a manner that adds value for their clients. Hence, in some sense, Infomediary acts as an intermediary between those who want the information and those who supply it. Infomediary helps customers on the information gathering process, where customers search for information regarding their intended purchases. These functions of Infomediary make the four "information" aspects - **Information source, Information quality, Information Product** and **Information Timeliness**, to be crucial factors in evaluating the success of Infomediary.

Information Quality On the **Information quality** aspect, the information must be ***accurate*** and ***valid*** so as to help user to make decision [32, 24, 2, 42, 72]. User must find the information to be *reliable* [31, 2] and *consistent*, i.e. the information must be dependable. [45, 31] Users receive Web information with certain degree of skepticism and are very dubious about the ***credibility*** of the information. On the contextual aspect of information quality, which means information quality (IQ) must be considered within the context of the task at hand [42]. The information should be ***relevant*** [32, 2, 45, 42]. Information should be *informative and valu-*

able in the sense that the information will enhance their purchasing decision. As mentioned in McKinney et al. [45], ***usefulness*** is one of the components in Information Quality for web customer satisfaction. Due to the importance of this criterion, it is chosen as the first means objective "Maximize product/ service information quality."

Information Source Moving to the **Information Source** aspect, customer expects that the Infomediary is a ***comprehensive*** information source and can compare product offerings from as many suppliers as possible. Besides, the variety of products or service should be great. Hence, customers concerns about the "scope" covered by the Infomediary. The extent of information, range of information and level of detail provided by Infomediary are crucial. The ***adequacy*** of information is also important [45]. Information supplied by Infomediary should be *sufficient, complete* [32, 2] and includes all necessary topics for the customers. This point is not mentioned in Keeney [38]. Hence, we add "Maximize information source" as the second means objective into the instrument.

Information Product The presentation format is an attribute that is stressed in literatures of UIS, EUCS. Data should be ***properly organized*** and in a ***useful format*** for the users to interpret data at ease [31, 24]. Infomediary, serves a function to aggregate product or service from different countries or regions of the world. However, there is the problem of representational differences. It needs to address the issues on ***representation*** – how to represent product/service; ***composition*** – what are the components for the product/ service; and ***recognition*** – what is the product it is really referring to. Based on the instrument developed by McKinney et al. [45], the information must also be clear in meaning, ease to read and understand. It is also mentioned in Siegel et al. [77]. In short, the ***understandability*** is very important. These components are then appended into the means objective "Maximize Information Product" in Keeney [38].

Information Timeliness The **timeliness of Information** is also another important information aspect in UIS, EUCS, EUISS, CIS [32, 24, 2, 72]. The changes in price among multiple suppliers should be most update. This is classified into the fourth means objective "Maximize product information timeliness".

Comparison Shopping Infomediary creates and adds value for the customer during several critical phases, from the initial search, supplier, and product comparison to actual transaction and ultimate product or service delivery [27]. Hence, supplier and product comparison is one of the attributes customers value when using Infomediary.

Ease of use All of the above are related to the information aspects of the Infomediary. Besides these constructs, system quality is also important since it would affect customer's preference to use Infomediary. Customers dissatisfied with the system performance of the Infomediary are likely to leave even if the information suggested by the Infomediary is of high quality. System quality pertaining to customer satisfaction also has practical implications for the design of Infomediary. So, on the system aspect, the Infomediary **us-**

ability is important in the sense that customers always expect Infomediary is *easy to use,* with a *simple layout* and has a *clear design.* This dimension has been emphasized in EUS, CIS [24, 72, 45]. This construct is already included in Keeney [38] as the means objective "Maximize ease of use".

System responsiveness Besides, user often expect system to be responsive enough so he does not have to spend time waiting for the information to be retrieved. It is quoted as an attribute of system quality in [2]. However, **system responsiveness** is often implemented at the price of compromising **information timeliness**, i.e. to achieve fast response to user request, Infomediary may cache extracted data in their systems, resulting in outdated information. Even if there is a daily update of the cache, it is not sufficient to avoid compromises on data timeliness because online prices change frequently. Due to its importance, it is included as one of the means objectives "Enhance system responsiveness".

Personalization and Interactivity Besides, customer searching for products and services would also probably like to have great access to information so as to facilitate their information gathering process. They expect easier search capabilities and hence, the Infomediary should be able to assist him to choose a product or service that suits his needs. In order to facilitate the information gathering process, and at the same time, to ensure the search results meet the customer need, the query generation should clearly *customize customer preference.* And customers concern about the personal design of the Infomediary, for example, the shopping cart feature. As quoted in McKinney et al. [45], *interactivity* is one of the key constructs for web customer satisfaction. This brings in a new means objective "Enhance Personalization and Interactivity".

Navigation The next add-in means objective is "Navigation". It is a crucial component in system quality. As we have explained before that Infomediary assists customers in the information gathering process, it is essential that Infomediary is easy to *navigate.* Customers expect that it should be easy to go back and forth between pages and only with a few clicks they can locate their desired information [45].

The above factors are taken into consideration for evaluating the success of Infomediary. A total of 29 objectives are identified after addition to and reclassification of objectives in Keeney [38]. 20 of them are means objectives while 9 are fundamental objectives. A total of 138 items were then produced to measure the success factors of Infomediary. There were 96 questions in the means objectives category measuring 20 constructs while 42 questions in the fundamental objectives measuring 9 constructs. The list of means and fundamental objectives is depicted in appendix A.1.

6.3 Relationships between Customer Values

Once the above objectives are categorized, it is useful to relate categories by means-ends relationships. We adopt the approach by Keeney [38]. We try to build a means-ends network to indicate the main means-ends relationships among the general objectives. In Fig. A.1, on the right is the set of fundamental objectives. The overall objective is to maximize customer satisfaction. Its component fundamental objectives collectively can be used to describe the complete value proposition of an Infomediary usage. The set of means objectives on the left indicates numerous categories in which changes could be made to alter the resulting value proposition.

6.4 Survey Instrument

The purpose of the survey was described as "To evaluate the value of infomediaries for electronic shopping based upon customer perceptions." Infomediary was defined as "the system delegated to monitor the Web sites of the information providers or electronic stores and search for the most relevant information or the best products based on the customer's requirement. For example, MySimon, BizRate, and Yahoo Shopping are infomediaries for general products, such as books, computers, electronic devices, clothing, and so on. Expedia, Priceline, and Travelocity are infomediaries for flight tickets, hotels and rental cars. After receiving the queries from customers, the system identifies all the relevant products or services based on the customer's requirements and the information it has aggregated from the potential vendors. The Infomediary present the resulted items in the order of price, vendors' reputation, the relevance of the items to customers' requirements, or weighted sum of several criteria."

6.4.1 Task File

In order to make sure respondents have the experience of using Infomediary, respondents have to finish one or more of three tasks which let them experience how the use of Infomediaries (e.g. Travelocity, Expedia, and Yahoo shopping) may help them to identify the best products that fit their needs. The tasks appear in the appendix D.

6.4.2 Questionnaire: Demographic Variables and Measures

The item generation process discussed before resulted in 138 items to measure the factors that influence Infomedairy success. The questionnaire was split into two parts. The first part are the 96 items relate to issues that influence respondent decision to use infomediaries for electronic shopping (i.e. means objectives). The second part consists of 42 items that relate to respondent objectives when using infomediaries (i.e. fundamental objectives). Items were not sorted and sub-headings were not used. A five-point Likert-type scale was used, where 1= not at all; 2 = a little; 3 = moderately; 4 = much; and 5 = a great deal, for questions related to means objectives; while 1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; and 5 = strongly agree, for response about fundamental objectives. The instructions asked respondents to think about their engagement with Infomediary and circle the response that best described their belief. Respondents were also asked to answer demographic questions about gender, age, level of use and reason of use and their amount of spending on internet shopping, etc. The composite self-administered questionnaire appears in the appendix D. A match between the means fundamental objectives and the item number in the survey is also included in the Fig. A.2.

6.4.3 Sample Description and Survey Administration

Survey Administration The survey was administered to graduate and undergraduate students in the Chinese University of Hong Kong, the University of Arizona, the Texas A and M University - College Station and also to professional in various fields. The same version of the questionnaire was used in both Hong Kong and the US since the program was in English and respondents felt comfortable responding to English version. Participation with the study was voluntary and respondents were given sufficient time to assess their responses. The completed questionnaires were either collected in person, or emailed or mailed in by the respondents later. A few filled questionnaires were discarded because of incomplete responses.

Sample characteristics A sample of 98 usable responses was obtained representing 36 males (36.7%) and 62 females (63.3%) from the US (22.4%) and Hong Kong (77.6%). Respondents fall into the following age distribution: less than 20 (5.1%), 20-29(82.7%), 30-39(10.2%), and greater than 40 (2.0%). 59.2% of the respondents shops online 0–1 times per month, 31.6% of them does it 1–5 times per month, while 4% shops online over 5 times per month. Respondents spend on average HKD$2,649 in a year (standard deviation HKD$8607). Before they make their purchase, 41.8% of them visits 1–5 electronic stores while 15.3% of them visits over 5 stores. 36.7% of the respondents uses infomediaries 1–5 times per month to assist their online shopping while 0.03% uses over infomediaries over 5 times per month.

Chapter 7

Data Analysis and Results

7.1 DATA ANALYSIS APPROACH

In our study, we are going to develop a measurement model to measure the factors that influence Infomediary success. The purpose of a measurement model is to describe how well the observed indicators serve as a measurement instrument for the latent variables (P.15) [35]. In our case, the latent variable is success of Infomediary. The data were analyzed with several objectives in mind: purification, unidimensionality, reliability, brevity, and simplicity of factor structure. Reliability is the extent to which an experiment, test, or any measuring procedure yields the same results on repeated trials.

7.1.1 Purification

First, we need to purify the items before factor analysis. Churchill [20] describes the need to purify before factor analysis on the data, i.e. to eliminate "garbage items", in the hope of determining the number of dimensions underlying the construct. The rationale behind is that when factor analysis is conducted before purification, the "garbage items" produce more dimensions than can be conceptually identified, thus, confounding the interpretation of the factor analysis.

Accordingly, for purification, the first step is to calculate the **item-to-total correlations** and **coefficient alpha**, which are used to delete garbage items [20, 22]. So, two independent criteria were used to eliminate items. First, items were eliminated if their corrected item-total correlation (the correlation of each item with the sum of the other items in its category) were less than 0.50. The support for this procedure is the domain-sampling model. The key assumption in this model is that all items, if they belong to the domain of the concept, have an equal amount of common core. If all the items in a measure are drawn from the domain of a single construct, responses to those items should be highly intercorrelated. The corrected-item-total correlation provides a measure of this [20].

The second step for item elimination is using *internal consistency reliability*. Internal consistency is the extent to which tests or procedures assess the same characteristic or quality. In our study, we analyze the internal consistency of the survey items dealing with the success factor of Infomediary in order to reveal the extent to which items on the questionnaire focus on the motion of value of Infomediary to customer. Hence, the reliability of items comprising each dimension was examined using Cronbach's alpha to see if additional items could be eliminated without substantially lowering reliability. This criterion for item purification has been used in other management information systems (MIS) studies [70]. In our study, items were eliminated if the reliability of the remaining items was at least 0.90. Where deleting either of two items that would have the same impact on Cronbach's alpha, the item with the higher correlated item-total correlation was retained.

7.1.2 Identification of Factor Structure

Types of Factor Analysis

After the above deletions, **an exploratory factor analysis** of the remaining items in each category was conducted to determine the factor structure of the entire set of items, and at the same time to assess the unidimensionality of the retained items for each group. There are two main kinds of factor analysis: Confirmatory Factor Analysis (CFA) and Exploratory Factor Analysis (EFA). Confirmatory Factor Analysis (CFA) is a kind of theory testing approach. It is based on strong theoretical or, empirical foundation. While the purpose of Exploratory Factor Analysis (EFA) is to identify the factor structure or model for a set of variables, i.e. how many factors exist and pattern of factor loadings. It also determines whether the factors are correlated or uncorrelated. The variables are free to load on all factors. It is a kind of theory generating method. Contrary to CFA, EFA is employed when only heuristic or weak literature exists. Hence, in our case, we choose to use EFA for the factor analysis. This method helps to identify factorially pure items that would facilitate the testing of more specific hypotheses [74], and to identify the components that make up the total measure [15] .

Principal Component Analysis and Factor Analysis

One of our aims in the instrument development process is brevity. We need to determine if there are a small number of underlying constructs which might account for the main sources of variation in our complex set of correlations (correlation between the large set of items). In our scale development, we assembled a number of items designed to measure some constructs (our methodology) i.e. to determine empirically how many dimensions (underlying constructs) account for most of the variance on an instrument (scale). The original variables in this case are the items on the scale. Hence we need some kinds of variables reduction scheme. If with adequate sample size an empirical approach is preferable. Two basic approaches are (1) principal component analysis and (2) factor analysis. In both approaches, a linear combination of the original variables are derived, and often a small number of these account for most of the variation or the pattern of correlation [64]. In factor analysis, mathematical model is set up, factor can only be estimated. Factor analysis tries to match the reconstructed correlations to the observed sample correlations. While component analysis is to transform the original variable into a new set of linear combination (the principal component), which account for as much as possible of the total variance [64, 7]. Stevens [64] quoted various literature view on the differences that will emerge if principal component is used in instead of factor analysis. It gives a concluding comments from the literature that when the number of variables is moderately large (say around 30), and the analysis contains virtually no variables expected to have low communalities (e.g. 0.4), then practically any of the factor procedures will lead to the same interpretation. The communality of a variable is the amount of variance on a variable accounted for by the set of factors. As both methods often yield similar results and since principal component analysis is a psychometrically sound procedure [64], we choose to examine the sample using the Principal Component Analysis as the extraction technique. The component analysis is on the covariance matrix.

Nature of Principal Component Analysis Principal Component Analysis is one form of EFA. The principle of Principal Component Analysis (PCA) is to find a linear combination of the variables which accounts for the maximum account of variance. For the first principal component, its variance is equal to the largest eigenvalue of the sample covariance matrix. The the procedure finds a second linear combination of, uncorrelated with the first component, such that it accounts for the next largest amount of variance (after the variance to the first component has been removed). Thus through the use of PCA, a set of correlated variables is transformed into a set of uncorrelated variables. [64]

Bartlett's sphericity test Bartlett's test of sphericity [21] tests the null hypothesis that the variables in the population correlation matrix are uncorrelated. If one fails to reject with this test, then there is no reason to do the factor analysis since the variables are already uncorrelated. So, before identifying the factor structure of the construct using factor analysis, we try to find out the chi-square of and significance level using **Bartlett's sphericity test**, so as to determine whether the intercorrelation matrix contains enough common variance to make factor analysis worth pursuing.

Criteria for deciding on how many components to retain As cited in [64], the most widely used criteria for deciding on how many components to retain is to retain only those components whose eigenvalues are greater than 1. This the rule proposed by Kaiser [36]. Stevens [64] quoted from studies in other literature that when number of variables is smaller than 30 and the communalities are greater than 0.7 or when number of respondents is greater than 250 and mean communality is greater than 0.6, this criterion is more accurate. The other criterion is scree plot [16]. It is a plot of magnitude of eigenvalue against ordinal number. Generally, the successive eigenvalue drops off sharply and then level off. The recommendation is to retain all eigenvalues in the sharp descent before the first one the line where they start to level off. When the sample size is greater than 200, scree plot is a good evaluation technique.

Since in our study, there are a total of 29 objectives and we have around 100 responses, we propose to use the first criteria - Kaiser rule, as the criterion if the communalities are greater than 0.7.

Factor Rotation - increase interpretability of factor There are two major classes of rotations available: orthogonal rotations, where the new factors are still uncorrelated, or oblique rotations, the new factors will be correlated. The decision for using which rotation is purely theoretically based - orthogonal rotation methods are based on the theoretical conceptualization of factors not being correlated, whereas oblique rotations allow factors to correlate. There are two types of orthogonal rotations. The Quartimax method - each variable loads only on one factor. However, it causes the problem that most of the variables tend to load on a single factor. The other is Varimax method [36]- each variable loads high on a smaller number of variables and low or very low on the other variables. It makes interpretation easier. However, the Varimax rotation destroys the maximum variance property. The first rotated factor will no longer necessarily account for the maximum amount of variance. Even though it is true, it is important to interpret the factors [64]. Penhazur and Schmekin [52] suggest to rotate both orthogonally and obliquely. When, on the basis of the latter, it is concluded that the correlations among the factors are negligible, the interpretation of the simpler orthogonal solution becomes tenable. In our study, we will employ the Varimax method as the orthogonal rotation, the most widely used method. In order to support its validity, we will test whether the correlations between factors are negligible.

Factor loading Factor loading is the component-variable correlation. It is simply the Pearson correlation between the variable and the factor (linear combination of the variables). It empirically clusters the variable. The loading which is going to be used to interpret a factor should be statistically significant at a minimum. To be significant means either the sample size is large (e.g. N=500 for 20 variables) or it passes the significant test. As suggested by Stevens [64], the rule for interpreting factors using factor loadings should take sample size into account. For a sample size of 100, the critical value of the correlation coefficient is 0.512. From the Monte Carlo study by

Guadagnoli and Velicer [28], components with four or more loadings above 0.6 in absolute value are reliable, regardless of sample size.

The use of imprecise and ambiguous terms to label factors was avoided. The items in each category were assumed to be measures of the same construct [3]. If the factor analysis revealed more than one factor, we had to determine whether to eliminate the additional factors or conclude that the construct was more complex than originally accepted. Items that were not factorially pure (loading on more than one factor at 0.30 or above) were also eliminated.

7.1.3 Construct validity

Construct validity seeks agreement between a theoretical concept and a specific measuring device or procedure. It can be broken down into two subcategories: convergent validity and discriminant validity. **Convergent validity** is the actual general agreement among ratings, gathered independently of one another, where measures should be theoretically related. **Discriminant validity** is the lack of relationship among measures which theoretically should not be related. In this study, correlation matrix for each instrument was analyzed for **convergent** and **discriminant validity** [24]. This approach to convergent validity tests if the correlations between measures of the same theoretical construct are different than zero and large enough to warrant further investigation. **Discriminant validity** is tested for each item by counting the number of times it correlates more highly with item of another factor than with items of its own theoretical variable. For discriminant validity, Campbell and Fiske [14] suggest that the count should be less than one-half of the potential comparisons.

After the above reliability and validity testing of the instrument, we can build a path model which shows the hypothesized or actual relationships among observed variables and the factors they are designed to measure.

7.2 RESEARCH FINDINGS

7.2.1 Descriptive statistics

Of the 96 items related to means objectives, 92 items reported a mean over 3, with only 4 items have a mean under but close to 3 (ranges from 2.87–2.96). All of the 42 items measuring fundamental objectives have means over 3. The mean, minimum, maximum and standard deviation of 138 items are shown in Table C.1.

Geographical impact Before we develop the instrument, we do an analysis to determine if there are significant differences between the responses from Hong Kong respondents (Group 1) and those from United States respondents (Group 2). We compared the means of 138 items between the Hong Kong group and the United States group. We attempted to find out if there is opposite trend between the means of two groups, i.e. for the same item, whether one group has mean below 3 while another has mean over 3. "3" is the mid-point of the scale which represents "moderately" and "neutral" for responses about means and fundamental objectives respectively. All of the items, (except Q53, Q94, Q96 and Q119) have means lied on the same side of the scale for both groups. For these 4 exceptions, the means cluster around the mid-point, with differences between two groups within 0.5. We further computed the 90% confidence intervals of the mean difference for each of the 138 items. The intervals lie between -1.186 and 1.195. Hence, the results suggested that the geographical difference has no significant impact to the instrument. The group statistics and the 90% confidence interval of the difference are shown in Table C.2 and C.3 respectively. We then proceed to the instrument development process.

7.2.2 Purification- Means Objectives

The item purification procedure, described above, allowed us to eliminate 35 out of the 96 items for the means objectives category because they have corrected item-total correlation below 0.5. Reliability analysis resulted in elimination of 3 more items. The elimination of these items individually causes an increase in Cronbach's alpha with the remaining items in that dimension. In the item-deletion procedures, all items in the constructs *product information*, *system security* and *personal transaction support* are eliminated. This resulted in the removal of these 3 dimensions. The list of items that are eliminated is depicted in Table 7.1. The 58 remaining items on 17 dimensions are further analyzed for the factor structure.

7.2.3 Factor Structure Identification- Means Objectives

Next, we proceeded with the dimensionality of the remaining constructs. An exploratory factor analysis was conducted for the remaining 58 items using

Item number	Corrected Item-total correlation	Item number	Corrected Item-total correlation
15	0.4004	16	0.3870
17	0.2732	33	0.4739
12	0.3136	13	0.2760
14	0.3250	24	0.3464
25	0.3935	26	0.3936
27	0.3774	28	0.3327
48	0.3705	49	0.2582
9	0.3092	10	0.4039
11	0.3659	38	0.4333
42	0.2911	61	0.4893
40	0.4327	71	0.1593
72	0.3721	5	0.4783
32	0.3408	6	-0.0513
7	0.3224	8	0.2336
87	0.4391	89	0.4444
92	0.4741	93	0.4853
94	0.0396	95	0.3591
96	0.1205		
Item number	Alpha if item deleted	Original alpha	
63	0.8571	0.8510	
70	0.8709	0.8673	
73	0.9132	0.8937	

Table 7.1: List of eliminated items in Means Objectives

Varimax as the rotation method. Bartlett's test of sphericity was 4594.022 ($p < 0.0001$). This suggests intercorrelation matrix contains enough variance to make factor analysis worth pursuing. Since the vast majority of the communalities are greater than 0.7 (only communalities of 6 items lies between 0.602 to 0.674), we use the Kaiser rule as the criterion for deciding the number of components to retain in the principal component analysis. Under this rule, 14 components are retained which explained 75.875% of the variance. 21 items with loadings larger than 0.30 on more than one factor, i.e. impure items, are deleted. After the impure items are deleted, the remaining items have strong factor loadings (i.e. larger than 0.512). The results suggested a 11-factor model with 37 items. 7 out of 11 factors are eliminated since the Hotelling test is not significant for these 7 sub-scales. After these eliminations, a 4-factor model consists of 21 items resulted. Using this data set, the corrected item-total correlation and Cronbach's alpha were calculated. The range for corrected item-total correlation was 0.6801 to 0.8467 for *online payment*, 0.5984 to 0.8345 for *navigation design*, 0.7212 to 0.7713 for *information relevance*, and 0.6490 to 0.8363 for *product choice*. Reliability statistics were 0.9273, 0.9146, 0.8640, and 0.8709 for *online payment*, *navigation design*, *information relevance* and *product choice* respectively. Overall reliability for the 21-item scale was 0.8600. The Hotelling test was significant for all 4 subscales ($p < 0.0175$) with F-values ranging from 2.6217 (for *navigation design*) to 4.7578 (for *product choice*). Hotelling tests are differences among the entire set of dependent variables. Table 7.2 provides details of the measures for items under these 4 subscales. The description of the items in the emerged instrument is listed in Table 7.3. In order to support the Vari-

New Item Code	Original Item Code	Factor loading	Corrected Item -total Correlation	Alpha	F-value
Online Payment				0.9273	3.7782
OP1	83	0.842	0.8467		
OP2	79	0.834	0.7309		
OP3	81	0.833	0.8342		
OP4	76	0.808	0.7206		
OP5	82	0.788	0.8056		
OP6	77	0.780	0.6801		
OP7	80	0.763	0.7724		
Navigation Design				0.9146	2.6217
ND1	46	0.863	0.8345		
ND2	45	0.822	0.8047		
ND3	47	0.818	0.7929		
ND4	44	0.814	0.7530		
ND5	56	0.773	0.7122		
ND6	43	0.715	0.6856		
ND7	55	0.699	0.6040		
ND8	54	0.640	0.5984		
Information Relevance				0.8640	4.2182
IR1	21	0.820	0.7713		
IR2	22	0.802	0.7375		
IR3	23	0.797	0.7212		
Product Choice				0.8709	4.7578
PC1	68	0.877	0.8363		
PC2	69	0.851	0.7814		
PC3	67	0.788	0.6490		

Table 7.2: Measures of new Factors for Means Objectives

max method is tenable, we performed the exploratory analysis using Direct Oblimin method - one kind of oblique rotation. The component correlation matrix was studied. We found out all of entries in the correlation was close to zero, with only 2 exceptions (the correlations are -0.349 and -0.351, which are close to 0.32). However, a further study indicated the components given rise to these exceptions will be eliminated due to the impurity of items. Hence, this supports the use of orthogonal rotation for exploratory factor analysis.

Item Code	Item description
Online Payment	
OP1	I am concerned about shipping errors.
OP2	I am concerned about my personal information being shared.
OP3	I worry about being charged inaccurately.
OP4	I am concerned about misuse of my personal information.
OP5	I am concerned about charging errors.
OP6	I am concerned about receiving unsolicited materials.
OP7	I am concerned about transaction error.
Navigation Design	
ND1	I feel that the infomediary systems have clear design.
ND2	I feel that the infomediary systems are well-organized.
ND3	I feel that the infomediary systems are user-friendly.
ND4	I feel that the infomediary systems are easy to use.
ND5	I feel that the infomediaries are easy to navigate.
ND6	I feel that the infomediaries have simple layout for their content.
ND7	I feel that it is easy to go back and forth between pages of the infomediary.
ND8	I feel that the description for each links on infomediaries are clear.
Information Relevance	
IR1	I feel that the information that I get from infomediaries is related to the purchase decision.
IR2	I feel that the information that I get from infomediaries is pertinent to the purchase decision.
IR3	I feel that the information that I get from infomediaries is relevant to the purchase decision.
Product Choice	
PC1	I like to have greater product choice.
PC2	I like to have greater product selection.
PC3	I like having maximum range of quality product options.

Table 7.3: Item description for instrument measuring Means Objectives

7.2.4 Construct validity- Means Objectives

The instrument's correlation matrix was analyzed for convergent and discriminant validity. Table C.4 represents the measure correlation matrix. The smallest within variable (factor) correlations are: *online payment* = 0.499 *navigation design* = 0.431, *information relevance* = 0.647, and *product choice* = 0.586. For a sample of 98, these are significantly ($p < 0.01$) different than zero and large enough to encourage further investigation of discriminant validity. Based on the examination of correlation matrix in table C.4 , there is no violation of the discriminant validity condition.

7.2.5 Purification- Fundamental Objectives

We proceed to the analysis of Fundamental Objectives. Following the same item purification procedures allows us to eliminate 8 out of the 42 items for the fundamental objectives category because they have corrected item-total correlation below 0.5. Reliability analysis resulted in elimination of 2 more items. The elimination of these items individually cause an increase in Cronbach's alpha with the remaining items in that dimension. In the item-deletion procedures, all items in the construct *Maximize privacy* are eliminated. This resulted in the removal of 1 dimension. The list of items that are eliminated is depicted in Table 7.4. The 32 remaining items on 8 dimensions are further analyzed for the factor structure.

Item number	Corrected Item-total correlation	
100	0.4634	
101	0.4695	
104	0.4951	
117	0.4305	
118	0.4305	
119	0.3818	
127	0.3941	
128	0.4038	
Item number	Alpha if item deleted	Original alpha
114	0.8774	0.8169
129	0.7651	0.7635

Table 7.4: List of eliminated items in Fundamental Objectives

7.2.6 Factor Structure Identification- Fundamental Objectives

Similar as the analysis conducted for means objectives, we continue with the dimensionality of the remaining constructs. An exploratory factor analysis was conducted for the remaining 32 items using Varimax as the rotation method. Bartlett's test of sphericity was 2315.664 ($p < 0.0001$). This suggests intercorrelation matrix contains enough variance to make factor analysis worth pursuing. Since the majority of the communalities are greater than 0.7 (only communalities of 8 items are less than 0.65 but over 0.55), we use the Kaiser rule as the criterion for deciding the number of components to retain in the principal component analysis. Under this rule, 8 components are retained which explained 74.925% of the variance. 13 items with loadings larger than 0.30 on more than one factor, i.e. impure items, are deleted. After the impure items are deleted, the remaining items have strong factor loadings (i.e. larger than 0.512). The results suggested a 8-factor model with 19 items. 2 out of 8 factors are eliminated since the Hotelling test is not significant for these 2 sub-scales. After these eliminations, a 6-factor model consisted of 13 items resulted. Using this data set, the corrected item-total correlation and Cronbach's alpha were calculated. The range for corrected item-total correlation was 0.5395 for *shopping enjoyment*, 0.6860 to 0.8246 for *transaction time*, 0.5569 to 0.7747 for *shopping convenience*, 0.6196 for *product value*, and 0.7815 for *cost*. Reliability statistics were 0.7002, 0.8752, 0.8177, 0.7651, and 0.8774 for *shopping enjoyment*, *transaction time*, *convenience*, *product value* and *cost* respectively. For the factor searching time, as it is a single item construct, no corrected item-total correlation and reliability statistics can be computed. Overall reliability for the 13-item scale was 0.8416. The Hotelling test was significant for 5 subscales ($p < 0.0155$) with F-values ranging from 5.8148 (for *transaction time*) to 14.9354 (for *shopping convenience*). Hotelling tests are differences among the entire set of dependent variables. Table 7.5 provides details of the measures for items under these 6 subscales. Besides, the item descriptions for items in this new instrument is listed in Table 7.6. In order to support the Varimax method is tenable, we performed the exploratory analysis using Direct Oblimin method - one of kind of oblique rotation. The component correlation matrix was studied. We found out all of entries in the correlation was close to zero, with only 2 exceptions (the correlations are 0.390 and -0.412). However, a further study indicated the components given rise to these exceptions will be eliminated due to the impurity of items. Hence, this bolsters the use of orthogonal rotation for exploratory factor analysis.

New Item Code	Original Item number	Factor loading	Corrected Item -total Correlation	Alpha	F-value
Shopping Enjoyment				0.7002	14.5882
SE1	123	0.884	0.5395		
SE2	121	0.741	0.5395		
Transaction Time				0.8752	5.8148
TT1	108	0.846	0.7733		
TT2	109	0.835	0.8246		
TT3	107	0.707	0.6860		
Shopping Convenience				0.8177	14.9354
SC1	98	0.887	0.7280		
SC2	97	0.855	0.7747		
SC3	99	0.623	0.5569		
Product Value				0.7651	6.9630
PV4	131	0.687	0.6196		
PV5	130	0.675	0.6196		
Cost				0.8774	6.0676
CO1	115	0.832	0.7815		
CO2	116	0.824	0.7815		
Searching Time					
ST	110	0.770			

Table 7.5: Measures of new Factors for Fundamental Objectives

7.2.7 Construct validity- Fundamental Objectives

The instrument's correlation matrix was analyzed for convergent and discriminant validity. Table C.5 represents the measure correlation matrix. The smallest within variable (factor) correlations are: *shopping enjoyment* = 0.540 *transaction time* = 0.620, *shopping convenience* = 0.501, *product value* = 0.620 and *cost* = 0.782. For a sample of 98, these are significantly ($p < 0.01$) different than zero and large enough to encourage further investigation of discriminant validity. Based on the examination of correlation matrix in table C.5, there is no violation of the discriminant validity condition.

New Item Code	Item Description
Shopping Enjoyment	
SE1	It is important to minimize regret of shopping.
SE2	It is important to inspire customer.
Transaction Time	
TT1	It is important to minimize queuing time.
TT2	It is important to minimize waiting time.
TT3	It Is important to minimize payment time.
Shopping Convenience	
SC1	It is important to maximize purchasing convenience.
SC2	It is important to maximize convenience.
SC3	It is important to minimize time pressure when shopping.
Product Value	
PV1	It is important to get the best product for the buck.
PV2	It is important to ensure quality of product.
Cost	
CO1	It is important to minimize tax cost.
CO2	It is important to minimize shipping cost.
Searching Time	
ST1	It is important to minimize time to find product.

Table 7.6: Item description for instrument measuring Fundamental Objectives

7.2.8 A Model for Measuring factors that Influence Infomediary Success

In sum, we have developed two instruments to measure the means objectives and fundamental objectives, which are critical factors that influence Infomediary success. The 4 factor, 21 item model for the means objectives,and the 6 factor, 13 item model for fundamental objectives, both are emerged from the purification process was demonstrated to produce acceptable reliability estimates, and evidence also supported its convergent validity and discriminant validity.

Chapter 8

Conclusions and Future Work

8.1 Implications, Limitations and Future Work - Collaborative Infomediary

Implications and Future Research Collaborative Infomediary is important for helping users to gain serendipity on top of ubiquitous access through World Wide Web. In this paper, we develop a system utilizing collaborative feedback on top of the fundamental functionality of user profile and user feedback, so that higher F-measure of information retrieval can be achieved. The user profiles provide us not only general knowledge of the user preferences, but also a comparison basis for similarity between the users. The "non-ratings" proximity measures design helps our system to overcome the traditional *sparsity* problem suffered by most of the memory based collaborative system. Combining the user profiles, user feedback and collaborative feedback produces the best performance. In the future research, we can further extend by migrating the system to the mobile version where users can benefits in using the system in PDA or mobile phone.

Limitations In the experiment we have conducted, around 10 subjects are recruited. The subject size may not be large enough. Another experiment of larger subject size may be used for evaluation of the system performance. Other than the performance measures we have used for the evaluation, we can assess the Collaborative Infomediary's performance from another perspective, such as the use of instruments of success factors, in which we can assess the user satisfaction on the Collaborative Infomediary.

8.2 Implications, Limitations and Future Work - Infomediary Success Factors

In measuring success of Infomediary, a critical task is to identify the key constructs of success, which is very often linked to satisfaction of the user, and to develop a validated instruments to measure them. Hence, this study have immediate implications for Infomediary on the Web and for research in success of Infomediary.

Implications Since online shopping becomes a common practice, Infomediary has emerged as an assistant for customer online shopping activities. Company operating as Infomediary needs to find out how to be successful in order to compete in the Internet market. The ultimate question about the success of Infomediary depends on how customers perceive its value.

Our study makes contribution to Internet Commerce by generating a list of items that cover different dimensions to measure the success of Infomediary - a kind of business model in Internet Commerce. The study employs an exploratory approach for the instrument development and follows widely accepted methodologies. The rigorous validation procedure brings out a parsimonious 4-factor, 21-item instrument for measuring means objectives and a 6-factor, 13-item instrument for measuring fundamental objectives. So, having access to reliable and scientifically tested metrics, the practitioners would be able to examine the structure and dimensionality of Infomediary success. Our proposed metrics can assist Infomediary company in this regard and help them to develop an effective design for the Infomediary. Besides, the validated measures could pave the way for researcher to investigate the success of Infomediary through formulation of means and fundamental objectives of customer using the Infomediary.

Limitations and Future Research The findings of this study discovered multidimensional measures of success factors that influence Infomediary users that are intuitively appealing and psychometrically reliable and valid. However, the sample size in use for instrument development may not be large enough. Other samples of larger size should be used for the validation of the instrument. Confirmatory analysis is also required for greater generalization of the novel instrument. Research to examine the second-order nature of these factors is also appropriate. It is plausible to expect a second order model for the proposed constructs. Our study suggests the four components for "means objectives" and the six components for the "fundamental constructs" constructs. Through further research employing confirmatory factor analysis can provide clearer picture of these concepts.

8.3 Conclusions

This thesis presents a Collaborative Infomediary which helped investors to search for relevant Chinese financial news online and its collaborative components is shown to have improvement over existing system in relevant news retrieval. On top of that, this thesis also reports the development of two instruments for measuring "means and fundamental objectives" for Infomediary. These instruments are reliable and can be used with confidence by academics and practitioners, and most importantly, should stimulate new research that has practical implications for how Infomediary are designed, developed and implemented.

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Appendix A

Means Objectives & Fundamental Objectives

A.1 List of Means Objectives & Fundamental Objectives

Means Objectives

1. Maximize product/service information quality
   - Maximize accuracy of information (re-classify)
   - Maximize the validity of information
   - Maximize the relevancy of information
   - Maximize the credibility of information
2. Maximize information source
   - Maximize the comprehensiveness of information source
3. Maximize information product
   - Maximize information about promotion
   - Maximize the information about product / service
   - Maximize available product information
   - Maximize the ease to identify the product refer to by Infomediary
   - Provide good textual representation of factual data
   - Provide clear description of product / Information

- Include all main information about product

4. Maximize product information timeliness
   - Keep track of prices changes among multiple suppliers
   - Ensure the product information timeliness
5. Enhance comparison shopping
   - Maximize products for comparison
   - Provide comparison shopping
   - Maximize ease of comparison shopping
   - Maximize speed of comparison shopping
6. Maximize ease of use
   - Maximize ease of user interface
   - Make access easy
   - Make search process easy
   - Simplify finding desired product
   - Maximize ease of purchase
7. Enhance personalization and interactivity
   - Have many search possibilities (re-classify)
   - Facilitate information gathering (re-classify)
   - Generate query for customer preference customization
   - Get more focused profile of what is of interest to you (re-classify)
8. Enhance system responsiveness
   - Maximize transaction speed
   - Minimize response time of system
9. Make better purchase choices
   - Minimize likelihood of disappointment
   - Maximize confidence
10. Maximize product variety and availability

- Increase variety of products
- Maximize product selection
- Have broad choice of products
- Maximize range of quality options

11. Minimize personal travel
    - Minimize travel distance
    - Minimize driving effort
12. Minimize misuse of credit card
    - Minimize unauthorized use of credit card
    - Maximize safety of credit card
13. Minimize misuse of personal information
    - Minimize receipt of unsolicited material
    - Minimize transfer of personal Information
14. Maximize accuracy of transaction
    - Minimize charging errors
    - Minimize shipping errors
    - Minimize product errors
15. Minimize fraud
    - Maximize fraud protection
    - Discourage/prevent fraud
    - Maximize seller legitimacy
    - Maximize Infomediary legitimacy
    - Maximize neutrality of Infomediary
16. Assure system security
    - Maximize security of transaction
    - Discourage hacking
17. Assure reliable delivery

- Provide reliable delivery
- Assure arrival of purchase

18. Limit impulsive buying
    - Minimize "unwanted" purchases
    - Control unreasonable buying

19. Offer personal interaction
    - Provide human customer support
    - Provide opportunity for personal interaction

20. Navigation
    - Maximize navigation entertainment
    - Have adequate links to information
    - Have clear description of links
    - Maximize ease to navigate

Fundamental Objectives

Overall Objective Maximize customer satisfaction

1. Maximize convenience
    - Maximize purchase convenience
    - Maximize time flexibility in purchasing
    - Provide quality after-sales service
    - Assure an easy return process
    - Minimize effort of shopping
    - Minimize personal hassale
    - Maximize ease of finding product
2. Minimize time spent
    - Minimize purchase time
    - Minimize processing time
    - Minimize payment time
    - Minimize queuing time
    - Minimize time to find product
    - Minimize search time
    - Minimize time to order product
    - Minimize time to gather information
    - Minimize time to select a product
3. Minimize cost
    - Minimize product cost
    - Minimize tax cost
    - Minimize shipping cost
4. Maximize privacy
    - Avoid electronic mailing lists
5. Maximize shopping enjoyment
    - Make shopping a social event

- Minimize worry
- Inspire customer
- Minimize regret
- Minimize disappointment
- Maximize customer confidence
- Reduce demand for forced labour

6. Maximize product quality
    - Maximize product value
    - Ensure quality of product
    - Get the best product for the buck
7. Minimize time to receive product
    - Minimize delivery time
    - Minimize shipping time
    - Minimize dispatch time
8. Maximize safety
    - Minimize risk of product use
9. Minimize environmental impact
    - Reduce environmental damages
    - Minimize pollution

Means-Ends Objectives Network for Infomediary

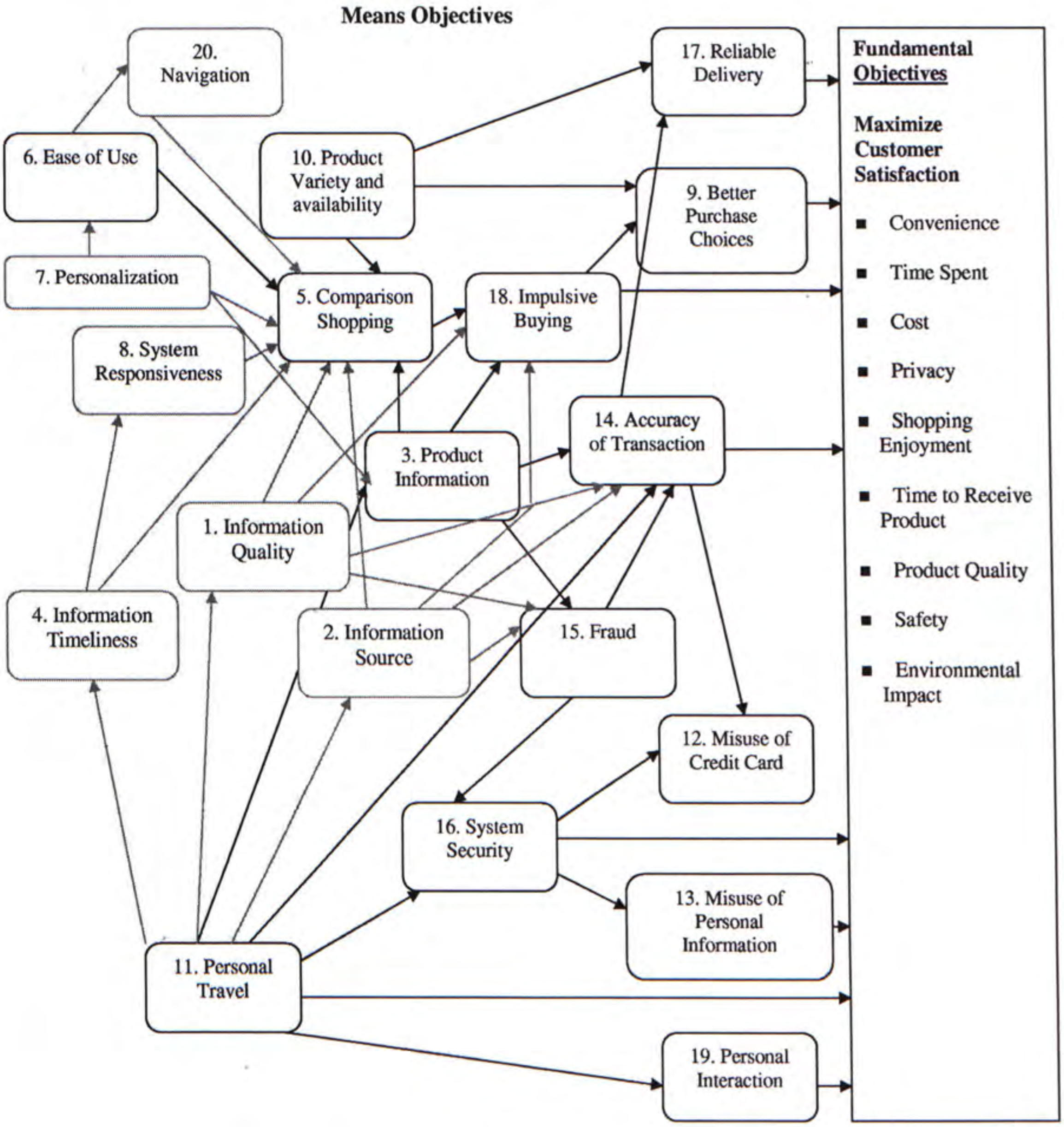


Figure A.1: Means-Ends relationship

Matching of items in survey to Means Objectives and Fundamental Objectives

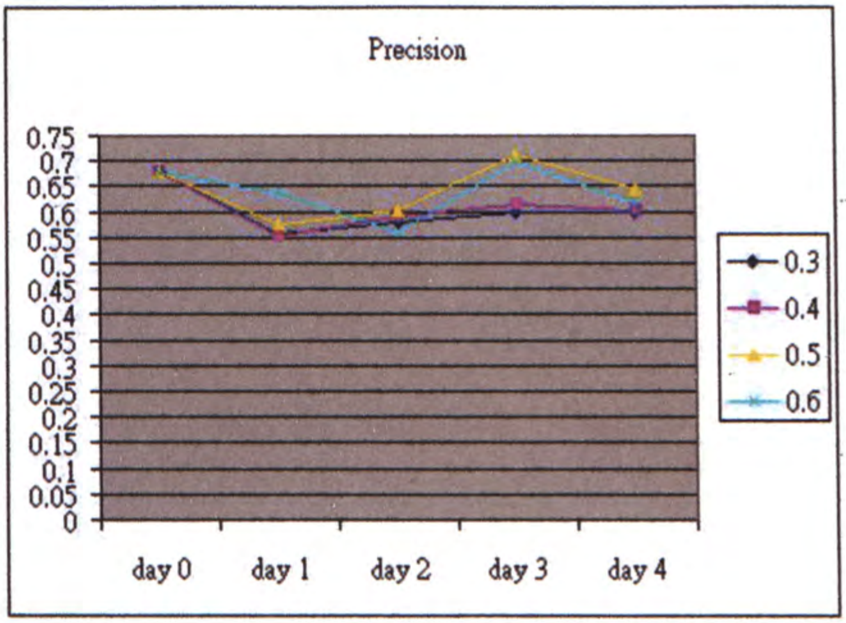
Means Objectives		Item number in survey
1	Information Quality	15,16,17,18,19,20,21,22,23,37
2	Information Source	29,30,31,33
3	Product Information	12,13,14,24,25,26,27,28
4	Information Timeliness	34,35,36
5	Comparison Shopping	63,64,65
6	Ease of Use	43,44,45,46,47,48,49,50
7	Personalization and Interactivity	9,10,11,38,42,57,58,59,60,61,62
8	System Responsiveness	39,40,41,71,72
9	Make better purchase choices	66
10	Maximize product variety and availability	67,68,69,70
11	Minimize personal travel	90,91
12	Minimize misuse of credit card	73,74,75
13	Minimize misuse of personal information	76,77,78,79
14	Maximize accuracy of transaction	80,81,82,83
15	Minimize fraud	1,2,3,4,5,32
16	Assure system security	6,7,8
17	Assure reliable delivery	87,88,89
18	Limit impulsive buying	84,85,86
19	Offer personal transaction	92,93,94,95,96
20	Navigation	51,52,53,54,55,56

Fundamental Objectives		Item number in survey
1	Maximize convenience	97-105
2	Minimize time spent	106-113
3	Minimize cost	114-116
4	Maximize privacy	117-118
5	Maximize shopping enjoyment	119-128
6	Maximize product quality	129-131
7	Minimize time to receive product	132-134
8	Maximize safety	135
9	Minimize environmental impact	136-138

Figure A.2: Match of Means Fundamental Objectives to Items in Survey

Appendix B

Statistical Results for Collaborative Infomediary Experiment



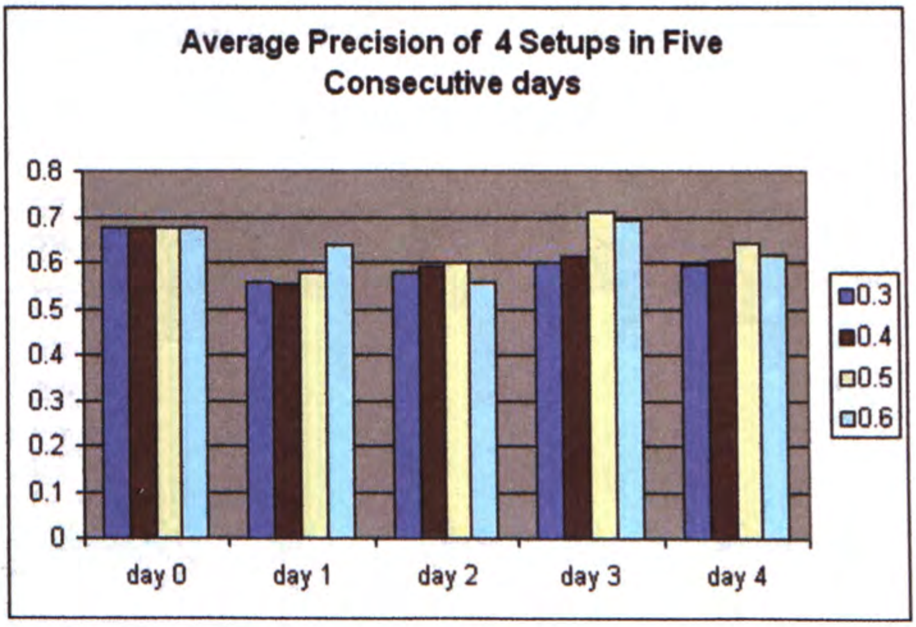


Figure B.1: Average Precision rates of 4 setups on 5 consecutive days

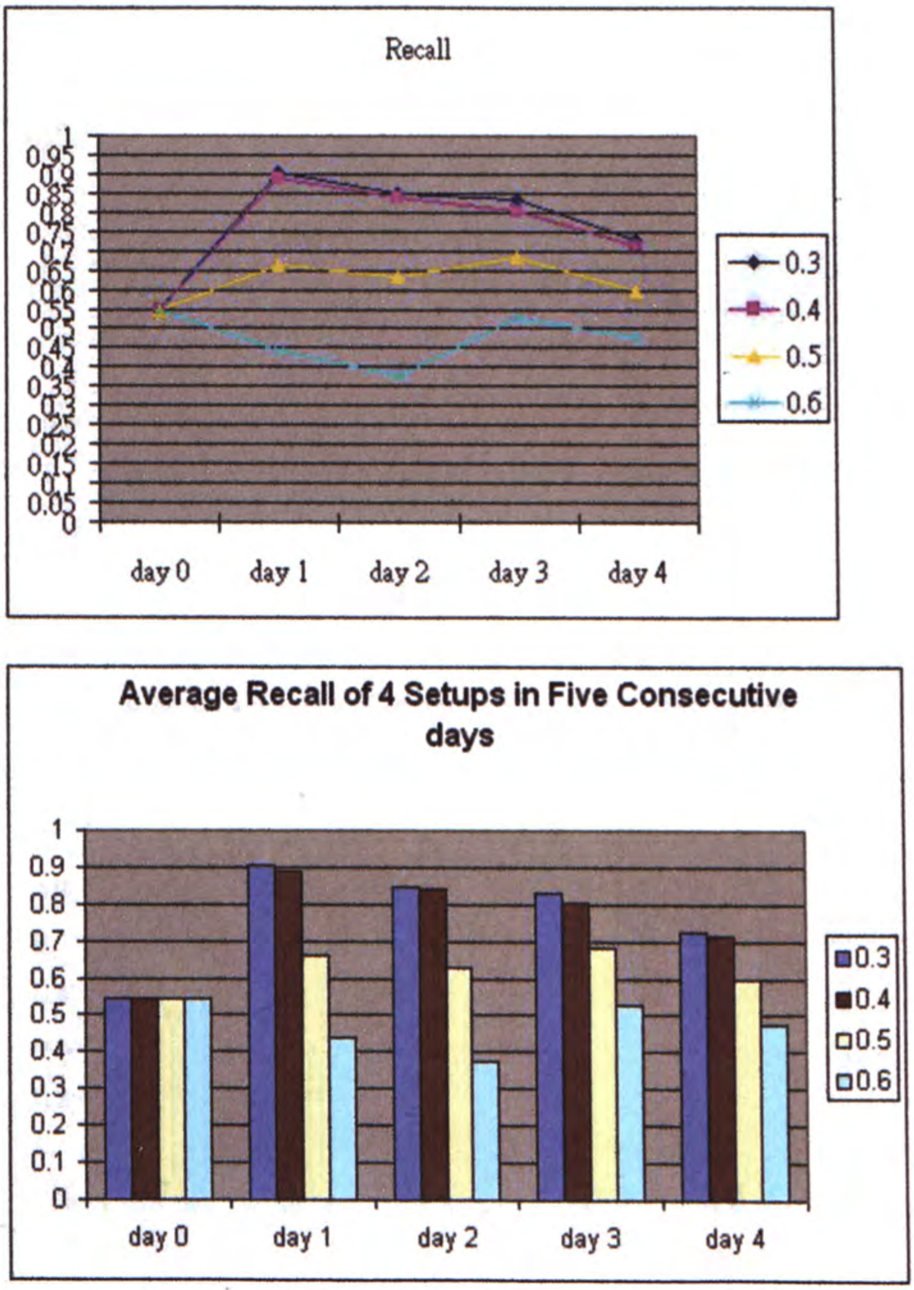
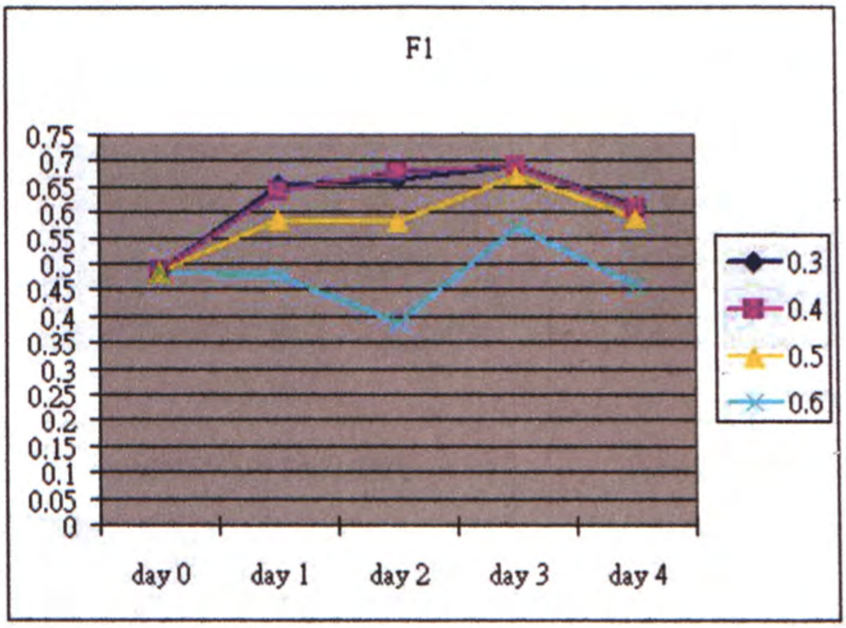


Figure B.2: Average Recall rates of 4 setups on 5 consecutive days



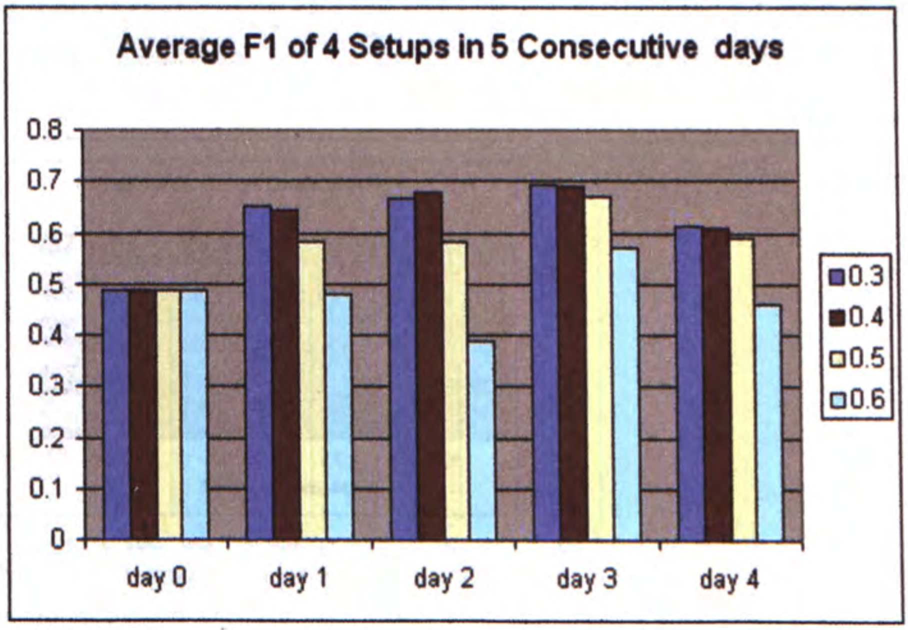


Figure B.3: Average F-measures of 4 setups on 5 consecutive days

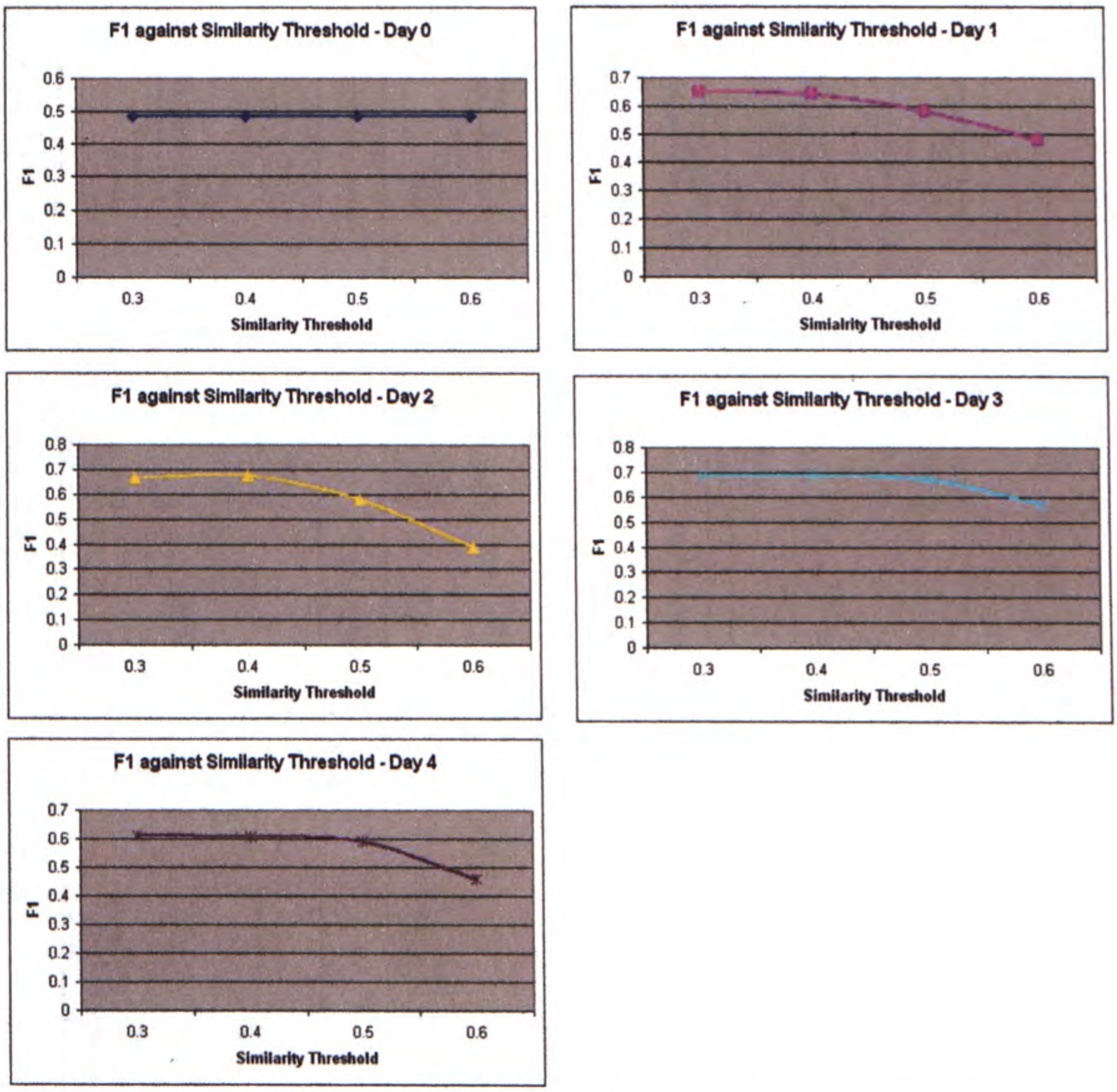


Figure B.4: F-measures against Similarity Thresholds for 5 consecutive days and aggregate of 5 consecutive days

F1

t-Test: Paired Two Sample for Means
day 1 F1 0.3 0.4

	Variable 1	Variable 2
Mean	0.652596885	0.642840718
Variance	0.045027878	0.040892315
Observations	8	8
Pearson Correlation	0.996154187	
Hypothesized Mean Difference	0	
df	7	
t Stat	1.331294701	
P(T<=t) one-tail	0.112405534	
t Critical one-tail	1.894578604	
P(T<=t) two-tail	0.224811067	
t Critical two-tail	2.364624251	

t-Test: Paired Two Sample for Means
day 1 0.4 0.5

	Variable 1	Variable 2
Mean	0.642840718	0.584329151
Variance	0.040892315	0.030526785
Observations	8	8
Pearson Correlation	0.752101024	
Hypothesized Mean Difference	0	
df	7	
t Stat	1.224267167	
P(T<=t) one-tail	0.130225971	
t Critical one-tail	1.894578604	
P(T<=t) two-tail	0.260451942	
t Critical two-tail	2.364624251	

t-Test: Paired Two Sample for Means
day 1 0.5 0.6

	Variable 1	Variable 2
Mean	0.584329151	0.478314856
Variance	0.030526785	0.01158633
Observations	8	8
Pearson Correlation	-0.154253314	
Hypothesized Mean Difference	0	
df	7	
t Stat	1.369850395	
P(T<=t) one-tail	0.106526761	
t Critical one-tail	1.894578604	
P(T<=t) two-tail	0.213053521	
t Critical two-tail	2.364624251	

t-Test: Paired Two Sample for Means
day 2 F1 0.3 0.4

	Variable 1	Variable 2
Mean	0.665840392	0.678729784
Variance	0.036187444	0.036331704
Observations	8	8
Pearson Correlation	0.975998429	
Hypothesized Mean Difference	0	
df	7	
t Stat	-0.873803499	
P(T<=t) one-tail	0.205598892	
t Critical one-tail	1.894578604	
P(T<=t) two-tail	0.411197783	
t Critical two-tail	2.364624251	

t-Test: Paired Two Sample for Means
day 2 0.4 0.5

	Variable 1	Variable 2
Mean	0.678729784	0.581876757
Variance	0.036331704	0.067121263
Observations	8	8
Pearson Correlation	0.601212311	
Hypothesized Mean Difference	0	
df	7	
t Stat	1.304865429	
P(T<=t) one-tail	0.116597559	
t Critical one-tail	1.894578604	
P(T<=t) two-tail	0.233195119	
t Critical two-tail	2.364624251	

t-Test: Paired Two Sample for Means
day 2 0.5 0.6

	Variable 1	Variable 2
Mean	0.581876757	0.387155032
Variance	0.067121263	0.050756988
Observations	8	8
Pearson Correlation	0.453420322	
Hypothesized Mean Difference	0	
df	7	
t Stat	2.161118335	
P(T<=t) one-tail	0.033748195	
t Critical one-tail	1.894578604	
P(T<=t) two-tail	0.067496389	
t Critical two-tail	2.364624251	

t-Test: Paired Two Sample for Means
day 3 0.3 0.4

	Variable 1	Variable 2
Mean	0.691634422	0.688692517
Variance	0.029476625	0.031592816
Observations	8	8
Pearson Correlation	0.979782266	
Hypothesized Mean Difference	0	
df	7	
t Stat	0.233434863	
P(T<=t) one-tail	0.411051602	
t Critical one-tail	1.894578604	
P(T<=t) two-tail	0.822103204	
t Critical two-tail	2.364624251	

t-Test: Paired Two Sample for Means
day 3 0.4 0.5

	Variable 1	Variable 2
Mean	0.688692517	0.670678833
Variance	0.031592816	0.04371886
Observations	8	8
Pearson Correlation	0.79099648	
Hypothesized Mean Difference	0	
df	7	
t Stat	0.39643618	
P(T<=t) one-tail	0.351795279	
t Critical one-tail	1.894578604	
P(T<=t) two-tail	0.703590558	
t Critical two-tail	2.364624251	

t-Test: Paired Two Sample for Means
day 3 0.5 0.6

	Variable 1	Variable 2
Mean	0.670678833	0.571786614
Variance	0.04371886	0.017995903
Observations	8	8
Pearson Correlation	0.800540957	
Hypothesized Mean Difference	0	
df	7	
t Stat	2.157644405	
P(T<=t) one-tail	0.033921749	
t Critical one-tail	1.894578604	
P(T<=t) two-tail	0.067843497	
t Critical two-tail	2.364624251	

Figure B.5: T-test for F-measures between adjacent similarity threshold setups

t-Test: Paired Two Sample for Means		
day 4 0.3 0.4		
	Variable 1	*Variable 2*
Mean	0.612021593	0.608451823
Variance	0.038454374	0.036473179
Observations	8	8
Pearson Correlation	0.997854674	
Hypothesized Mean Difference	0	
df	7	
t Stat	0.738580201	
P(T<=t) one-tail	0.242091862	
t Critical one-tail	1.894578604	
P(T<=t) two-tail	0.484183724	
t Critical two-tail	2.364624251	

t-Test: Paired Two Sample for Means		
day 4 0.4 0.5		
	Variable 1	*Variable 2*
Mean	0.608451823	0.590463614
Variance	0.036473179	0.046638611
Observations	8	8
Pearson Correlation	0.945049977	
Hypothesized Mean Difference	0	
df	7	
t Stat	0.708510473	
P(T<=t) one-tail	0.250767144	
t Critical one-tail	1.894578604	
P(T<=t) two-tail	0.501534289	
t Critical two-tail	2.364624251	

t-Test: Paired Two Sample for Means		
day 4 0.5 0.6		
	Variable 1	*Variable 2*
Mean	0.590463614	0.459545369
Variance	0.046638611	0.045322321
Observations	8	8
Pearson Correlation	0.262162181	
Hypothesized Mean Difference	0	
df	7	
t Stat	1.421527046	
P(T<=t) one-tail	0.099074383	
t Critical one-tail	1.894578604	
P(T<=t) two-tail	0.198148767	
t Critical two-tail	2.364624251	

day 1- day 4		
t-Test: Paired Two Sample for Means		
	Variable 1	*Variable 2*
Mean	0.655523323	0.65467871
Variance	0.034532761	0.033842895
Observations	32	32
Pearson Correlation	0.987013201	
Hypothesized Mean Difference	0	
df	31	
t Stat	0.160026656	
P(T<=t) one-tail	0.436949132	
t Critical one-tail	1.695518742	
P(T<=t) two-tail	0.873898265	
t Critical two-tail	2.039513438	

t-Test: Paired Two Sample for Means		
	Variable 1	*Variable 2*
Mean	0.65467871	0.606837089
Variance	0.033842895	0.043865371
Observations	32	32
Pearson Correlation	0.747822933	
Hypothesized Mean Difference	0	
df	31	
t Stat	1.909772493	
P(T<=t) one-tail	0.032726853	
t Critical one-tail	1.695518742	
P(T<=t) two-tail	0.065453705	
t Critical two-tail	2.039513438	

t-Test: Paired Two Sample for Means		
	Variable 1	*Variable 2*
Mean	0.606837089	0.474200468
Variance	0.043865371	0.032847874
Observations	32	32
Pearson Correlation	0.403581277	
Hypothesized Mean Difference	0	
df	31	
t Stat	3.495502685	
P(T<=t) one-tail	0.000725209	
t Critical one-tail	1.695518742	
P(T<=t) two-tail	0.001450418	
t Critical two-tail	2.039513438	

Figure B.6: T-test for F-measures between adjacent similarity threshold setups -*continued*

Appendix C

Statistical Results for Measuring Factors that influence success of Infomediary

Table C.1: Descriptive statistics for 138 items in the survey

Item	N	Minimum	Maximum	Mean	Std. Deviation
Q1	98	1	5	4.1429	0.885
Q2	98	1	5	4.1122	1.0243
Q3	98	1	5	3.7857	0.9659
Q4	98	2	5	4.0714	0.7898
Q5	98	2	5	4.0204	0.8732
Q6	98	1	5	3.2551	0.8653
Q7	98	2	5	4.1837	0.8039
Q8	98	1	5	3.9592	1.0043
Q9	98	2	5	4.1939	0.8453
Q10	98	2	5	3.4898	0.8154
Q11	98	2	5	3.4184	0.8486
Q12	98	2	5	3.9388	0.7841
Q13	98	1	5	3.8367	1.0122
Q14	98	1	5	3.9184	0.9810
Q15	98	3	5	4.5714	0.6735
Q16	98	3	5	4.2959	0.7210
Q17	98	2	5	4.0408	0.8485
Q18	98	1	5	3.2755	0.7431
Q19	98	2	5	3.2959	0.7351
Q20	98	2	5	3.4286	0.8249
Q21	98	2	5	3.7245	0.7002
Q22	98	2	5	3.5918	0.7439
Q23	98	2	5	3.7653	0.7839

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Table C.1: Descriptive statistics-*continued*

Item	N	Minimum	Maximum	Mean	Std. Deviation
Q24	98	2	5	3.4898	0.7897
Q25	98	2	5	3.5306	0.8520
Q26	98	1	5	4.0306	0.8180
Q27	98	2	5	3.9388	0.7296
Q28	98	2	5	3.5204	0.7212
Q29	98	1	5	3.0714	0.7496
Q30	98	1	5	2.9592	0.8112
Q31	98	1	5	2.9388	0.7841
Q32	98	2	5	3.8878	0.9293
Q33	98	2	5	3.3571	0.7898
Q34	98	2	5	4.0918	0.8862
Q35	98	1	5	4.0204	0.8613
Q36	98	2	5	4.0000	0.8615
Q37	98	2	5	3.6327	0.7376
Q38	98	1	5	3.3469	0.7194
Q39	98	1	5	3.2857	0.8615
Q40	98	2	5	3.3061	0.8174
Q41	98	1	5	3.2653	0.8916
Q42	98	2	5	3.4388	0.7470
Q43	98	1	5	3.2449	0.8003
Q44	98	1	5	3.3776	0.8061
Q45	98	1	5	3.4082	0.8596
Q46	98	1	5	3.3980	0.8821
Q47	98	1	5	3.4694	0.8758
Q48	98	2	5	4.0000	0.8495
Q49	98	2	5	3.9694	0.8550
Q50	98	1	5	3.3980	0.8341
Q51	98	1	5	3.0918	0.9204
Q52	98	1	5	2.8673	0.8926
Q53	98	1	5	3.0816	0.8081
Q54	98	1	5	3.1122	0.9068
Q55	98	1	5	3.2653	0.9476
Q56	98	1	5	3.2755	0.9057
Q57	98	2	5	3.6837	0.7943
Q58	98	2	5	3.5918	0.7576
Q59	98	1	5	3.7857	0.9222
Q60	98	1	5	3.5816	0.8843
Q61	98	2	5	3.8776	0.8998
Q62	98	1	5	3.6633	0.9075
Q63	98	2	5	4.0714	0.8996
Q64	98	2	5	4.0102	0.8433
Q65	98	1	5	4.0102	0.8793
Q66	98	2	5	3.7041	0.8520
Q67	98	2	5	3.7959	0.7593

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Table C.1: Descriptive statistics-*continued*

Item	N	Minimum	Maximum	Mean	Std. Deviation
Q68	98	2	5	3.9796	0.7992
Q69	98	2	5	4.0102	0.7929
Q70	98	2	5	3.9592	0.7984
Q71	98	2	5	4.2347	0.8348
Q72	98	1	5	3.6837	0.8921
Q73	98	1	5	4.4286	0.9525
Q74	98	1	5	4.5918	0.7711
Q75	98	1	5	4.6122	0.8327
Q76	98	2	5	4.4796	0.8401
Q77	98	1	5	4.2245	0.9254
Q78	98	1	5	4.1837	1.0087
Q79	98	2	5	4.4694	0.9328
Q80	98	1	5	4.2347	1.0234
Q81	98	1	5	4.2857	1.0051
Q82	98	1	5	4.1939	1.0320
Q83	98	1	5	4.1224	1.0480
Q84	98	1	5	3.4082	1.1739
Q85	98	1	5	3.3776	1.0984
Q86	98	1	5	3.4082	1.0920
Q87	98	1	5	3.9592	1.0246
Q88	98	1	5	3.9082	0.9315
Q89	98	2	5	4.0204	0.8849
Q90	98	1	5	3.4796	1.0957
Q91	98	1	5	3.3878	1.0417
Q92	98	1	5	3.9184	0.9597
Q93	98	1	5	3.8163	0.9880
Q94	98	1	5	3.0306	0.9133
Q95	98	1	5	3.5408	1.0271
Q96	98	1	5	2.9286	1.0077
Q97	98	2	5	4.2857	0.7180
Q98	98	2	5	4.2551	0.6783
Q99	98	1	5	3.8571	0.8967
Q100	98	1	5	4.2653	0.8562
Q101	98	1	5	4.2041	0.8118
Q102	98	2	5	3.6939	0.9014
Q103	98	2	5	4.0816	0.7416
Q104	98	2	5	3.9082	0.8134
Q105	98	2	5	4.2959	0.7210
Q106	98	2	5	4.0510	0.8295
Q107	98	2	5	3.8673	0.8203
Q108	98	2	5	4.0612	0.8473
Q109	98	2	5	4.0918	0.8134
Q110	98	2	5	4.1735	0.7868
Q111	98	2	5	4.1224	0.8766

continued on next page

Table C.1: Descriptive statistics-*continued*

Item	N	Minimum	Maximum	Mean	Std. Deviation
Q112	98	2	5	3.9592	0.8363
Q113	98	2	5	3.7653	0.9394
Q114	98	1	5	4.1531	0.8538
Q115	98	1	5	4.0204	0.9304
Q116	98	1	5	4.1735	0.9309
Q117	98	2	5	4.4082	0.7843
Q118	98	1	5	3.9898	0.9896
Q119	98	1	5	3.2653	1.0310
Q120	98	1	5	3.7755	0.9142
Q121	98	1	5	3.5918	0.8833
Q122	98	1	5	3.6122	0.8076
Q123	98	1	5	3.9286	0.9333
Q124	98	1	5	3.9286	0.9443
Q125	98	2	5	3.8878	0.9293
Q126	98	2	5	4.1327	0.8077
Q127	98	1	5	3.8163	0.8039
Q128	98	1	5	4.2551	0.8533
Q129	98	1	5	3.9694	0.8670
Q130	98	1	5	4.4184	0.8363
Q131	98	2	5	4.2245	0.8315
Q132	98	1	5	4.1633	0.8579
Q133	98	1	5	4.1224	0.8282
Q134	98	1	5	4.1020	0.8433
Q135	98	1	5	4.1122	0.9068
Q136	98	1	5	3.8061	1.0518
Q137	98	1	5	3.8776	0.9767
Q138	98	1	5	3.7959	1.0645

Table C.2: Group statistics for 138 items in the survey

Item	Demographic	N	Mean	Std. Deviation	Std. Error Mean
Q1	1	77	4.08	0.9	0.103
	2	21	4.38	0.805	0.176
Q2	1	77	4.23	0.916	0.104
	2	21	3.67	1.278	0.279
Q3	1	77	3.86	0.869	0.099
	2	21	3.52	1.25	0.273
Q4	1	77	4.17	0.677	0.077
	2	21	3.71	1.056	0.23
Q5	1	77	4.03	0.873	0.1
	2	21	4	0.894	0.195
Q6	1	77	3.22	0.883	0.101
	2	21	3.38	0.805	0.176
Q7	1	77	4.29	0.704	0.08

continued on next page

Table C.2: Group statistics-*continued*

Item	Demographic	N	Mean	Std. Deviation	Std. Error Mean
	2	21	3.81	1.03	0.225
Q8	1	77	4.06	0.908	0.103
	2	21	3.57	1.248	0.272
Q9	1	77	4.22	0.837	0.095
	2	21	4.1	0.889	0.194
Q10	1	77	3.52	0.805	0.092
	2	21	3.38	0.865	0.189
Q11	1	77	3.49	0.853	0.097
	2	21	3.14	0.793	0.173
Q12	1	77	3.96	0.785	0.09
	2	21	3.86	0.793	0.173
Q13	1	77	3.96	0.924	0.105
	2	21	3.38	1.203	0.263
Q14	1	77	4.04	0.895	0.102
	2	21	3.48	1.167	0.255
Q15	1	77	4.52	0.7	0.08
	2	21	4.76	0.539	0.118
Q16	1	77	4.36	0.687	0.078
	2	21	4.05	0.805	0.176
Q17	1	77	4.13	0.801	0.091
	2	21	3.71	0.956	0.209
Q18	1	77	3.27	0.737	0.084
	2	21	3.29	0.784	0.171
Q19	1	77	3.25	0.764	0.087
	2	21	3.48	0.602	0.131
Q20	1	77	3.31	0.831	0.095
	2	21	3.86	0.655	0.143
Q21	1	77	3.62	0.708	0.081
	2	21	4.1	0.539	0.118
Q22	1	77	3.44	0.698	0.08
	2	21	4.14	0.655	0.143
Q23	1	77	3.62	0.779	0.089
	2	21	4.29	0.561	0.122
Q24	1	77	3.4	0.815	0.093
	2	21	3.81	0.602	0.131
Q25	1	77	3.42	0.864	0.098
	2	21	3.95	0.669	0.146
Q26	1	77	4.01	0.786	0.09
	2	21	4.1	0.944	0.206
Q27	1	77	3.87	0.714	0.081
	2	21	4.19	0.75	0.164
Q28	1	77	3.47	0.754	0.086
	2	21	3.71	0.561	0.122
Q29	1	77	3.09	0.747	0.085

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Table C.2: Group statistics-*continued*

Item	Demographic	N	Mean	Std. Deviation	Std. Error Mean
	2	21	3	0.775	0.169
Q30	1	77	2.97	0.794	0.091
	2	21	2.9	0.889	0.194
Q31	1	77	2.95	0.776	0.088
	2	21	2.9	0.831	0.181
Q32	1	77	3.88	0.888	0.101
	2	21	3.9	1.091	0.238
Q33	1	77	3.36	0.776	0.088
	2	21	3.33	0.856	0.187
Q34	1	77	4.13	0.879	0.1
	2	21	3.95	0.921	0.201
Q35	1	77	4.01	0.769	0.088
	2	21	4.05	1.161	0.253
Q36	1	77	4.05	0.809	0.092
	2	21	3.81	1.03	0.225
Q37	1	77	3.58	0.767	0.087
	2	21	3.81	0.602	0.131
Q38	1	77	3.34	0.736	0.084
	2	21	3.38	0.669	0.146
Q39	1	77	3.27	0.868	0.099
	2	21	3.33	0.856	0.187
Q40	1	77	3.25	0.83	0.095
	2	21	3.52	0.75	0.164
Q41	1	77	3.25	0.934	0.106
	2	21	3.33	0.73	0.159
Q42	1	77	3.39	0.746	0.085
	2	21	3.62	0.74	0.161
Q43	1	77	3.18	0.823	0.094
	2	21	3.48	0.68	0.148
Q44	1	77	3.34	0.852	0.097
	2	21	3.52	0.602	0.131
Q45	1	77	3.4	0.907	0.103
	2	21	3.43	0.676	0.148
Q46	1	77	3.42	0.937	0.107
	2	21	3.33	0.658	0.144
Q47	1	77	3.48	0.94	0.107
	2	21	3.43	0.598	0.13
Q48	1	77	4	0.858	0.098
	2	21	4	0.837	0.183
Q49	1	77	4.01	0.835	0.095
	2	21	3.81	0.928	0.203
Q50	1	77	3.43	0.834	0.095
	2	21	3.29	0.845	0.184
Q51	1	77	3.18	0.914	0.104

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Table C.2: Group statistics-*continued*

Item	Demographic	N	Mean	Std. Deviation	Std. Error Mean
	2	21	2.76	0.889	0.194
Q52	1	77	2.94	0.879	0.1
	2	21	2.62	0.921	0.201
Q53	1	77	3.12	0.858	0.098
	2	21	2.95	0.59	0.129
Q54	1	77	3.05	0.972	0.111
	2	21	3.33	0.577	0.126
Q55	1	77	3.34	0.954	0.109
	2	21	3	0.894	0.195
Q56	1	77	3.32	0.952	0.108
	2	21	3.1	0.7	0.153
Q57	1	77	3.65	0.791	0.09
	2	21	3.81	0.814	0.178
Q58	1	77	3.6	0.73	0.083
	2	21	3.57	0.87	0.19
Q59	1	77	3.74	0.894	0.102
	2	21	3.95	1.024	0.223
Q60	1	77	3.6	0.862	0.098
	2	21	3.52	0.981	0.214
Q61	1	77	3.78	0.927	0.106
	2	21	4.24	0.7	0.153
Q62	1	77	3.75	0.876	0.1
	2	21	3.33	0.966	0.211
Q63	1	77	3.96	0.895	0.102
	2	21	4.48	0.814	0.178
Q64	1	77	3.91	0.846	0.096
	2	21	4.38	0.74	0.161
Q65	1	77	3.99	0.835	0.095
	2	21	4.1	1.044	0.228
Q66	1	77	3.62	0.889	0.101
	2	21	4	0.632	0.138
Q67	1	77	3.77	0.759	0.087
	2	21	3.9	0.768	0.168
Q68	1	77	3.97	0.811	0.092
	2	21	4	0.775	0.169
Q69	1	77	4	0.811	0.092
	2	21	4.05	0.74	0.161
Q70	1	77	3.97	0.811	0.092
	2	21	3.9	0.768	0.168
Q71	1	77	4.16	0.889	0.101
	2	21	4.52	0.512	0.112
Q72	1	77	3.68	0.88	0.1
	2	21	3.71	0.956	0.209
Q73	1	77	4.47	0.912	0.104

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Table C.2: Group statistics-*continued*

Item	Demographic	N	Mean	Std. Deviation	Std. Error Mean
	2	21	4.29	1.102	0.24
Q74	1	77	4.66	0.661	0.075
	2	21	4.33	1.065	0.232
Q75	1	77	4.69	0.712	0.081
	2	21	4.33	1.155	0.252
Q76	1	77	4.57	0.733	0.084
	2	21	4.14	1.108	0.242
Q77	1	77	4.26	0.865	0.099
	2	21	4.1	1.136	0.248
Q78	1	77	4.17	1.005	0.115
	2	21	4.24	1.044	0.228
Q79	1	77	4.56	0.851	0.097
	2	21	4.14	1.153	0.252
Q80	1	77	4.35	0.885	0.101
	2	21	3.81	1.365	0.298
Q81	1	77	4.44	0.803	0.091
	2	21	3.71	1.419	0.31
Q82	1	77	4.35	0.839	0.096
	2	21	3.62	1.431	0.312
Q83	1	77	4.23	0.944	0.108
	2	21	3.71	1.309	0.286
Q84	1	77	3.49	1.108	0.126
	2	21	3.1	1.375	0.3
Q85	1	77	3.44	1.07	0.122
	2	21	3.14	1.195	0.261
Q86	1	77	3.44	1.057	0.121
	2	21	3.29	1.231	0.269
Q87	1	77	4.13	0.879	0.1
	2	21	3.33	1.278	0.279
Q88	1	77	3.96	0.865	0.099
	2	21	3.71	1.146	0.25
Q89	1	77	3.96	0.895	0.102
	2	21	4.24	0.831	0.181
Q90	1	77	3.36	1.134	0.129
	2	21	3.9	0.831	0.181
Q91	1	77	3.22	1.059	0.121
	2	21	4	0.707	0.154
Q92	1	77	3.94	0.964	0.11
	2	21	3.86	0.964	0.21
Q93	1	77	3.91	0.948	0.108
	2	21	3.48	1.078	0.235
Q94	1	77	2.96	0.865	0.099
	2	21	3.29	1.056	0.23
Q95	1	77	3.58	0.978	0.111

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Table C.2: Group statistics-*continued*

Item	Demographic	N	Mean	Std. Deviation	Std. Error Mean
	2	21	3.38	1.203	0.263
Q96	1	77	2.86	0.899	0.102
	2	21	3.19	1.327	0.29
Q97	1	77	4.21	0.732	0.083
	2	21	4.57	0.598	0.13
Q98	1	77	4.21	0.675	0.077
	2	21	4.43	0.676	0.148
Q99	1	77	3.78	0.912	0.104
	2	21	4.14	0.793	0.173
Q100	1	77	4.19	0.889	0.101
	2	21	4.52	0.68	0.148
Q101	1	77	4.1	0.836	0.095
	2	21	4.57	0.598	0.13
Q102	1	77	3.64	0.916	0.104
	2	21	3.9	0.831	0.181
Q103	1	77	4.05	0.759	0.087
	2	21	4.19	0.68	0.148
Q104	1	77	3.74	0.768	0.088
	2	21	4.52	0.68	0.148
Q105	1	77	4.25	0.746	0.085
	2	21	4.48	0.602	0.131
Q106	1	77	4	0.889	0.101
	2	21	4.24	0.539	0.118
Q107	1	77	3.81	0.828	0.094
	2	21	4.1	0.768	0.168
Q108	1	77	4.08	0.855	0.097
	2	21	4	0.837	0.183
Q109	1	77	4.05	0.857	0.098
	2	21	4.24	0.625	0.136
Q110	1	77	4.09	0.814	0.093
	2	21	4.48	0.602	0.131
Q111	1	77	4.04	0.91	0.104
	2	21	4.43	0.676	0.148
Q112	1	77	3.87	0.848	0.097
	2	21	4.29	0.717	0.156
Q113	1	77	3.64	0.958	0.109
	2	21	4.24	0.7	0.153
Q114	1	77	4.05	0.872	0.099
	2	21	4.52	0.68	0.148
Q115	1	77	3.9	0.926	0.106
	2	21	4.48	0.814	0.178
Q116	1	77	4.03	0.959	0.109
	2	21	4.71	0.561	0.122
Q117	1	77	4.42	0.801	0.091

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Table C.2: Group statistics-*continued*

Item	Demographic	N	Mean	Std. Deviation	Std. Error Mean
	2	21	4.38	0.74	0.161
Q118	1	77	3.94	1.03	0.117
	2	21	4.19	0.814	0.178
Q119	1	77	3.36	0.931	0.106
	2	21	2.9	1.3	0.284
Q120	1	77	3.7	0.947	0.108
	2	21	4.05	0.74	0.161
Q121	1	77	3.58	0.848	0.097
	2	21	3.62	1.024	0.223
Q122	1	77	3.64	0.793	0.09
	2	21	3.52	0.873	0.19
Q123	1	77	3.79	0.894	0.102
	2	21	4.43	0.926	0.202
Q124	1	77	3.81	0.918	0.105
	2	21	4.38	0.921	0.201
Q125	1	77	3.77	0.887	0.101
	2	21	4.33	0.966	0.211
Q126	1	77	4.13	0.801	0.091
	2	21	4.14	0.854	0.186
Q127	1	77	3.71	0.776	0.088
	2	21	4.19	0.814	0.178
Q128	1	77	4.17	0.894	0.102
	2	21	4.57	0.598	0.13
Q129	1	77	3.84	0.859	0.098
	2	21	4.43	0.746	0.163
Q130	1	77	4.31	0.892	0.102
	2	21	4.81	0.402	0.088
Q131	1	77	4.08	0.839	0.096
	2	21	4.76	0.539	0.118
Q132	1	77	4.05	0.902	0.103
	2	21	4.57	0.507	0.111
Q133	1	77	4.04	0.88	0.1
	2	21	4.43	0.507	0.111
Q134	1	77	4.03	0.888	0.101
	2	21	4.38	0.59	0.129
Q135	1	77	4.05	0.902	0.103
	2	21	4.33	0.913	0.199
Q136	1	77	3.83	1.044	0.119
	2	21	3.71	1.102	0.24
Q137	1	77	3.86	0.956	0.109
	2	21	3.95	1.071	0.234
Q138	1	77	3.79	1.043	0.119
	2	21	3.81	1.167	0.255

Table C.3: 90 % Confidence Interval of Mean Difference for 138 items in the survey

Item	Mean Difference	Std. Error Difference	90% Confidence Interval	
			Lower	Upper
Q1	-0.3	0.217	-0.663	0.057
Q2	0.57	0.247	0.157	0.977
Q3	0.33	0.237	-0.06	0.726
Q4	0.45	0.19	0.139	0.77
Q5	0.03	0.216	-0.333	0.385
Q6	-0.16	0.213	-0.515	0.194
Q7	0.48	0.193	0.156	0.797
Q8	0.49	0.243	0.089	0.898
Q9	0.13	0.209	-0.221	0.472
Q10	0.14	0.201	-0.196	0.473
Q11	0.35	0.207	0.007	0.694
Q12	0.1	0.194	-0.218	0.426
Q13	0.58	0.243	0.176	0.984
Q14	0.56	0.236	0.171	0.955
Q15	-0.24	0.165	-0.516	0.031
Q16	0.32	0.175	0.025	0.607
Q17	0.42	0.206	0.074	0.757
Q18	-0.01	0.184	-0.318	0.292
Q19	-0.23	0.18	-0.529	0.07
Q20	-0.55	0.196	-0.872	-0.219
Q21	-0.47	0.166	-0.748	-0.195
Q22	-0.7	0.17	-0.983	-0.42
Q23	-0.66	0.182	-0.964	-0.36
Q24	-0.41	0.191	-0.724	-0.09
Q25	-0.54	0.204	-0.875	-0.199
Q26	-0.08	0.202	-0.418	0.254
Q27	-0.32	0.178	-0.615	-0.025
Q28	-0.25	0.177	-0.54	0.047
Q29	0.09	0.185	-0.217	0.399
Q30	0.07	0.201	-0.264	0.402
Q31	0.04	0.194	-0.279	0.365
Q32	-0.02	0.23	-0.404	0.36
Q33	0.03	0.195	-0.294	0.355
Q34	0.18	0.219	-0.185	0.54
Q35	-0.03	0.213	-0.389	0.319
Q36	0.24	0.212	-0.109	0.594
Q37	-0.23	0.181	-0.526	0.076
Q38	-0.04	0.178	-0.339	0.252
Q39	-0.06	0.213	-0.415	0.293
Q40	-0.28	0.2	-0.61	0.056
Q41	-0.09	0.22	-0.453	0.28
Q42	-0.23	0.183	-0.534	0.075

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Table C.3: 90% Confidence Interval-*continued*

Item	Mean Difference	Std. Error Difference	90% Confidence Interval	
			Lower	Upper
Q43	-0.29	0.196	-0.619	0.031
Q44	-0.19	0.199	-0.516	0.144
Q45	-0.03	0.213	-0.379	0.327
Q46	0.08	0.218	-0.28	0.445
Q47	0.05	0.217	-0.308	0.412
Q48	0	0.21	-0.349	0.349
Q49	0.2	0.211	-0.146	0.553
Q50	0.14	0.206	-0.199	0.485
Q51	0.42	0.224	0.048	0.791
Q52	0.32	0.219	-0.047	0.679
Q53	0.16	0.199	-0.166	0.495
Q54	-0.28	0.223	-0.651	0.088
Q55	0.34	0.232	-0.048	0.723
Q56	0.23	0.223	-0.141	0.6
Q57	-0.16	0.196	-0.485	0.165
Q58	0.03	0.187	-0.285	0.337
Q59	-0.21	0.227	-0.589	0.165
Q60	0.07	0.219	-0.29	0.437
Q61	-0.46	0.218	-0.82	-0.097
Q62	0.42	0.22	0.054	0.786
Q63	-0.52	0.216	-0.874	-0.156
Q64	-0.47	0.203	-0.809	-0.135
Q65	-0.11	0.217	-0.469	0.253
Q66	-0.38	0.207	-0.721	-0.032
Q67	-0.14	0.187	-0.45	0.173
Q68	-0.03	0.198	-0.354	0.302
Q69	-0.05	0.196	-0.373	0.278
Q70	0.07	0.197	-0.259	0.397
Q71	-0.37	0.203	-0.705	-0.031
Q72	-0.04	0.221	-0.406	0.328
Q73	0.18	0.235	-0.208	0.572
Q74	0.33	0.188	0.017	0.641
Q75	0.35	0.203	0.018	0.692
Q76	0.43	0.203	0.091	0.766
Q77	0.16	0.228	-0.215	0.544
Q78	-0.07	0.25	-0.484	0.345
Q79	0.42	0.227	0.039	0.792
Q80	0.54	0.247	0.131	0.952
Q81	0.73	0.237	0.333	1.122
Q82	0.73	0.244	0.326	1.137
Q83	0.52	0.254	0.098	0.941
Q84	0.4	0.288	-0.079	0.876
Q85	0.3	0.27	-0.15	0.747

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Table C.3: 90% Confidence Interval-*continued*

Item	Mean Difference	Std. Error Difference	90% Confidence Interval	
			Lower	Upper
Q86	0.16	0.27	-0.292	0.604
Q87	0.8	0.24	0.398	1.195
Q88	0.25	0.229	-0.134	0.627
Q89	-0.28	0.217	-0.638	0.084
Q90	-0.54	0.265	-0.982	-0.1
Q91	-0.78	0.245	-1.186	-0.372
Q92	0.08	0.237	-0.316	0.472
Q93	0.43	0.24	0.033	0.832
Q94	-0.32	0.224	-0.696	0.047
Q95	0.2	0.253	-0.217	0.624
Q96	-0.33	0.247	-0.744	0.077
Q97	-0.36	0.174	-0.652	-0.075
Q98	-0.22	0.166	-0.497	0.055
Q99	-0.36	0.219	-0.727	0
Q100	-0.33	0.209	-0.676	0.018
Q101	-0.47	0.195	-0.792	-0.143
Q102	-0.27	0.221	-0.636	0.099
Q103	-0.14	0.183	-0.442	0.165
Q104	-0.78	0.185	-1.09	-0.477
Q105	-0.23	0.177	-0.523	0.064
Q106	-0.24	0.204	-0.577	0.1
Q107	-0.29	0.201	-0.624	0.044
Q108	0.08	0.21	-0.27	0.426
Q109	-0.19	0.2	-0.519	0.147
Q110	-0.39	0.191	-0.702	-0.069
Q111	-0.39	0.213	-0.744	-0.035
Q112	-0.42	0.203	-0.752	-0.079
Q113	-0.6	0.224	-0.974	-0.229
Q114	-0.47	0.206	-0.814	-0.13
Q115	-0.58	0.222	-0.95	-0.211
Q116	-0.69	0.219	-1.053	-0.324
Q117	0.03	0.194	-0.288	0.357
Q118	-0.26	0.243	-0.66	0.149
Q119	0.46	0.251	0.042	0.875
Q120	-0.35	0.223	-0.717	0.025
Q121	-0.03	0.219	-0.398	0.328
Q122	0.11	0.2	-0.219	0.444
Q123	-0.64	0.222	-1.004	-0.268
Q124	-0.58	0.226	-0.951	-0.2
Q125	-0.57	0.223	-0.937	-0.197
Q126	-0.01	0.2	-0.345	0.319
Q127	-0.48	0.193	-0.797	-0.156
Q128	-0.4	0.207	-0.747	-0.059

continued on next page

Table C.3: 90% Confidence Interval-*continued*

Item	Mean Difference	Std. Error Difference	90% Confidence Interval	
			Lower	Upper
Q129	-0.58	0.206	-0.927	-0.242
Q130	-0.5	0.201	-0.831	-0.165
Q131	-0.68	0.194	-1.005	-0.363
Q132	-0.52	0.206	-0.861	-0.178
Q133	-0.39	0.201	-0.724	-0.056
Q134	-0.35	0.206	-0.696	-0.014
Q135	-0.28	0.223	-0.651	0.088
Q136	0.12	0.26	-0.315	0.549
Q137	-0.1	0.241	-0.496	0.306
Q138	-0.02	0.263	-0.455	0.42

	Q76	Q77	Q79	Q80	Q81	Q82	Q83	Q43	Q44	Q45	Q46	Q47	Q54	Q55	Q56	Q21	Q22	Q23	Q67	Q68	Q69
Q76	1.000																				
Q77	0.563	1.000																			
Q79	0.828	0.677	1.000																		
Q80	0.503	0.586	0.499	1.000																	
Q81	0.617	0.551	0.603	0.746	1.000																
Q82	0.522	0.504	0.526	0.767	0.860	1.000															
Q83	0.647	0.609	0.626	0.751	0.749	0.807	1.000														
Q43	0.084	0.036	0.038	-0.071	-0.152	-0.120	0.001	1.000													
Q44	0.110	-0.004	0.064	-0.084	-0.122	-0.114	-0.055	0.686	1.000												
Q45	0.112	0.143	0.183	0.042	0.007	0.049	0.093	0.603	0.728	1.000											
Q46	0.143	0.079	0.209	0.033	0.010	-0.006	0.069	0.635	0.700	0.830	1.000										
Q47	0.139	0.136	0.220	0.025	0.045	0.001	0.015	0.570	0.710	0.811	0.797	1.000									
Q54	0.037	0.142	0.071	0.027	-0.081	-0.079	-0.015	0.431	0.435	0.483	0.549	0.530	1.000								
Q55	0.240	0.131	0.219	0.201	0.179	0.137	0.112	0.444	0.448	0.448	0.489	0.432	0.445	1.000							
Q56	0.123	0.098	0.053	0.141	0.026	0.019	0.073	0.503	0.506	0.556	0.597	0.550	0.527	0.719	1.000						
Q21	-0.124	-0.031	-0.116	-0.110	-0.092	-0.125	-0.080	0.269	0.241	0.154	0.196	0.230	0.147	0.080	0.137	1.000					
Q22	-0.096	0.075	-0.033	-0.157	-0.146	-0.151	-0.067	0.239	0.208	0.134	0.140	0.171	0.237	0.111	0.138	0.712	1.000				
Q23	-0.062	-0.026	-0.158	-0.175	-0.176	-0.147	-0.065	0.306	0.256	0.190	0.136	0.222	0.197	0.126	0.237	0.689	0.647	1.000			
Q67	0.026	0.066	0.049	-0.017	0.023	-0.002	-0.007	0.168	0.178	0.145	0.246	0.146	0.183	0.191	0.113	0.165	0.143	0.057	1.000		
Q68	0.245	0.271	0.207	0.145	0.187	0.217	0.261	0.105	0.108	0.117	0.172	0.073	0.089	0.143	0.136	0.174	0.125	0.091	0.656	1.000	
Q69	0.256	0.264	0.230	0.175	0.229	0.174	0.185	0.093	0.107	0.145	0.186	0.156	0.170	0.120	0.082	0.079	0.007	-0.046	0.586	0.830	1.000

Table C.4: Correlations matrix for Means Objectives measures

	Q121	Q123	Q107	Q108	Q109	Q97	Q98	Q99	Q130	Q131	Q115	Q116	Q110
Q121	1.000												
Q123	0.540	1.000											
Q107	0.166	0.082	1.000										
Q108	0.254	0.058	0.620	1.000									
Q109	0.168	0.022	0.683	0.800	1.000								
Q97	0.202	0.077	0.450	0.276	0.325	1.000							
Q98	0.107	0.045	0.321	0.170	0.181	0.823	1.000						
Q99	0.277	0.160	0.408	0.351	0.372	0.560	0.501	1.000					
Q130	0.220	0.303	0.097	0.167	0.261	0.177	0.173	0.190	1.000				
Q131	0.238	0.207	0.301	0.244	0.381	0.340	0.208	0.265	0.620	1.000			
Q115	0.098	0.156	0.355	0.391	0.474	0.408	0.204	0.127	0.320	0.261	1.000		
Q116	0.024	0.074	0.219	0.352	0.469	0.342	0.158	0.079	0.316	0.349	0.782	1.000	
Q110	0.103	0.256	0.355	0.309	0.442	0.368	0.283	0.284	0.265	0.381	0.319	0.395	1.000

Table C.5: Correlations matrix for Fundamental Objectives measures

Appendix D

Survey Task File & Questionnaire

The following tasks are optional. If you are familiar with the infomediaries such as Travelocity, Expedia, and Yahoo Shopping, please go to the survey directly. If you have not used any of these infomediaries, please follow the instructions of the below tasks and experience how they may help you to identify the best products that fit your needs. Once you have tried one or more tasks and understand how they help you on purchase decisions, please go to the survey.

Task A

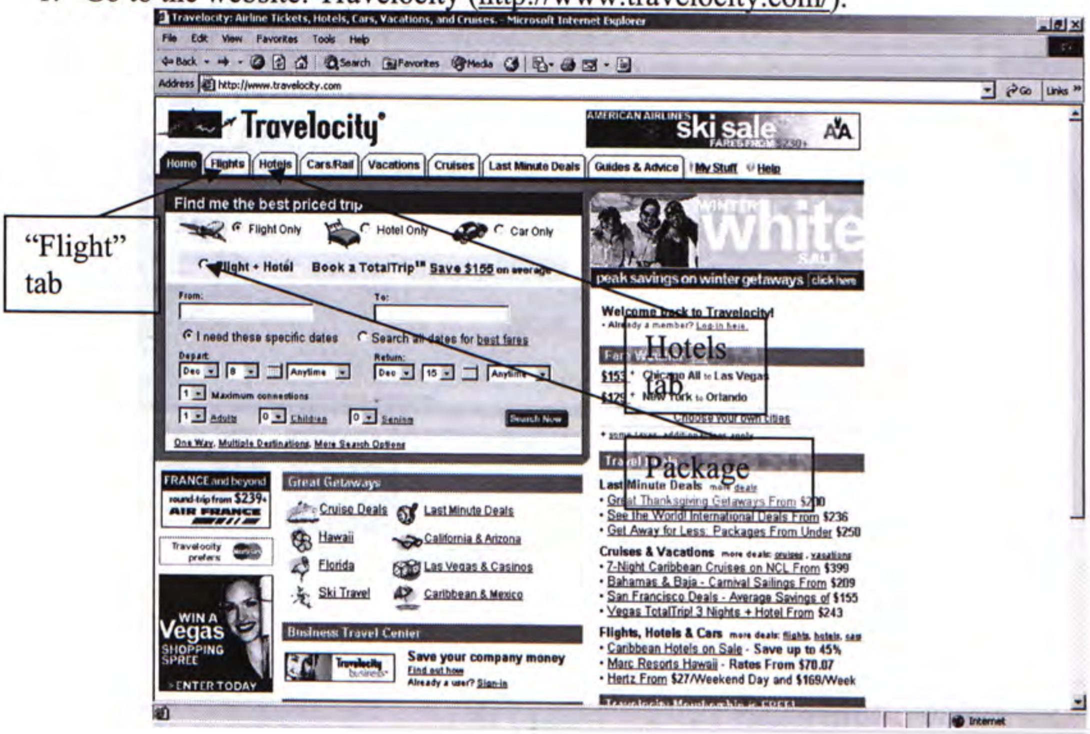
Infomediary:
Travelocity (http://www.travelocity.com/)

Scenario:
Suppose you are a graduate student of University of Texas, Austin and you live in Austin, Texas (TX). You have to attend the ISOneWorld Conference, from April 14 to April 16, 2004. The conference will be held in Las Vegas, Nevada (NV). (More information about the conference can be found from the website: http://www.isoneworld.org/). You plan to leave Austin on April 13, evening and return on April 17.

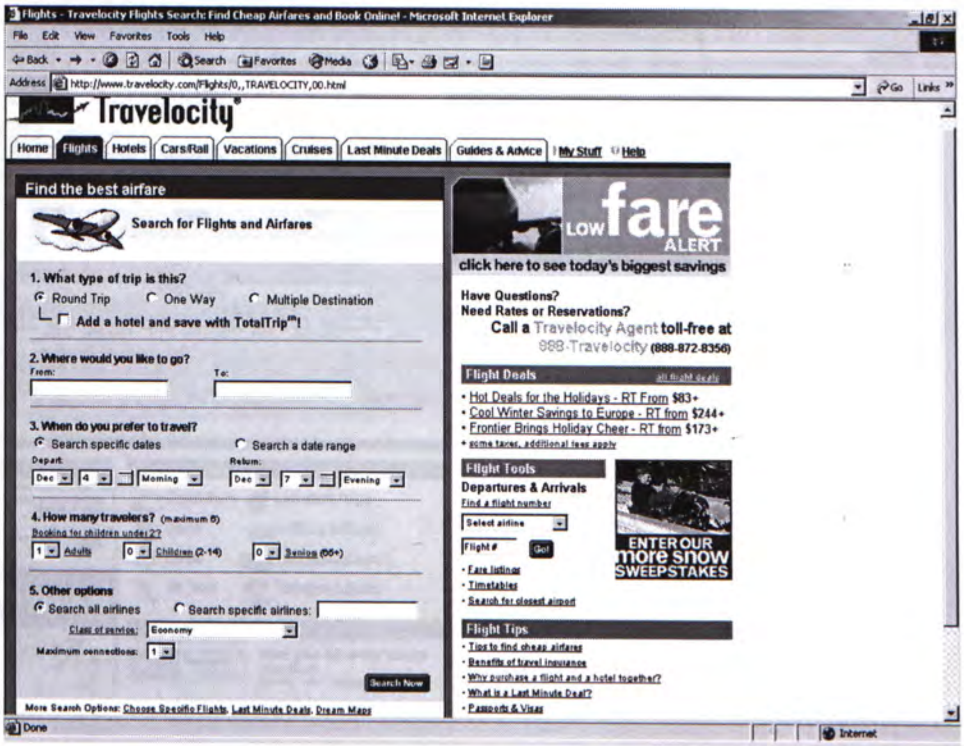
Your task is to arrange for the round trip flight and lodging for attending the conference. You plan to use the Infomediary: Travelocity (http://www.travelocity.com/) for making the flight and lodging reservations.

Guidelines:
The instructions below will guide you through the information gathering and purchasing process using the Infomediary, Travelocity.

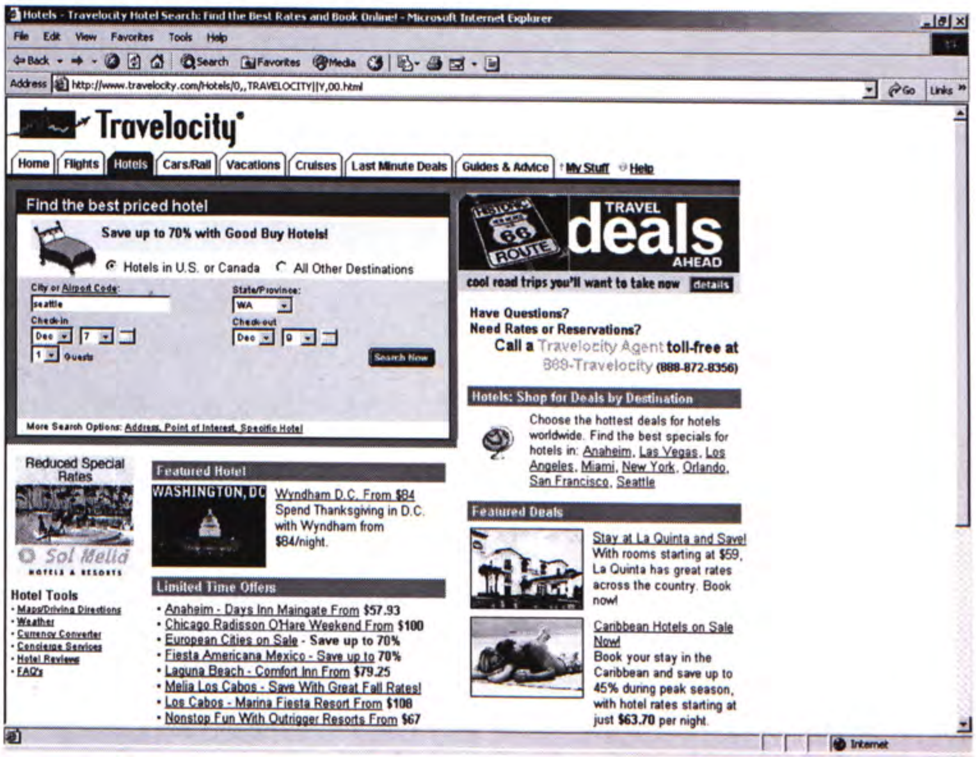
1. Go to the website: Travelocity (http://www.travelocity.com/).



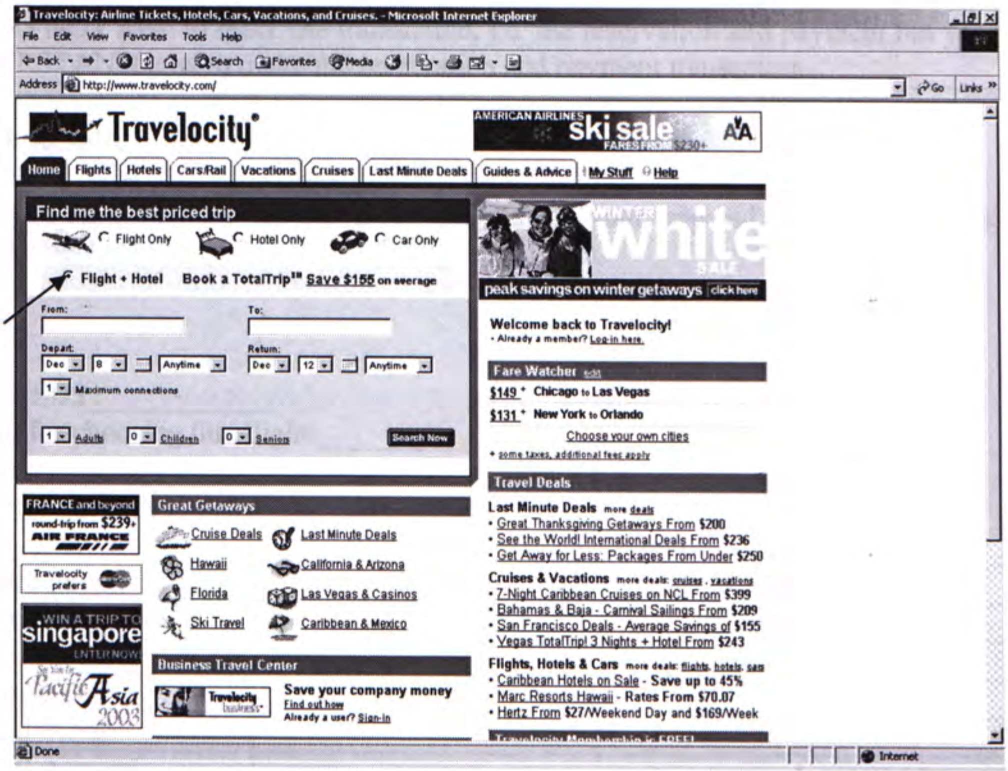
2. For flight information, you can select the "Flights" tab and then the following screen will appear. Enter details about departure city and date, destination city and date. After you submit your search, a list of flights that fit your requirements will be shown.



3. For the lounge information, you can select the "Hotels" tab and then the following screen will appear. Enter details about city, the check in and checkout date. After you submit your search, a list of hotels that fit your requirements will be shown.



4. Alternatively, you can enquire about the travel package (flights plus hotels) by selecting the button beside the "Flight + Hotel". And then enter your trip details.



5. Determine which airlines and hotels you would choose after doing the comparisons.

Reminder: You DO NOT have to make the transaction, i.e. the reservation and payment but you need to UNDERSTAND how to make the reservation and payment transaction.

Search Results

After you have finished the searching and chosen your targeted flights and hotels, please enter the details of your choice for the flight and hotel.

Flight:

Price: USD$___________
Reason for choosing this flight:____

- Outbound flight

Flight number:	
Airline:	
Departure Time:	
Departure Airport:	
Arrival Time:	
Arrival Airport:	
Other details: (Non-stop or details of stop)	
Travel time:	

- Return flight

Flight number:	
Airline:	
Departure Time:	
Departure Airport:	
Arrival Time:	
Arrival Airport:	
Other details: (Non-stop or details of stop)	
Travel time:	

Hotel:
Reason for choosing this hotel: ____

Hotel name:	
Hotel address:	
Room details:	
Nightly rate / total rates	

Task B

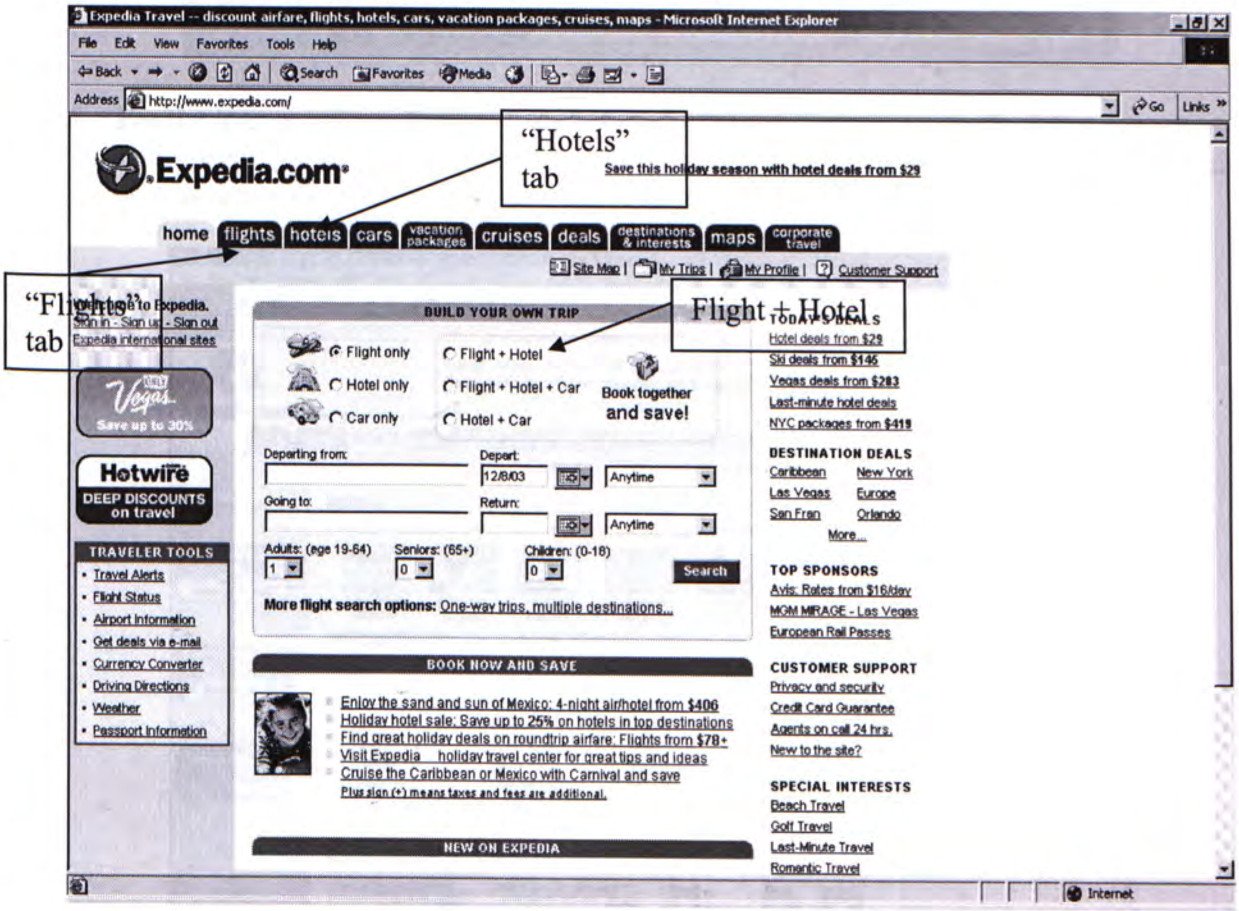
Infomediary:
Expedia (http://www.expedia.com/)

Scenario:
Suppose you are a graduate student of University of Texas, Austin and you live in Austin, Texas (TX). You have to attend the ISOneWorld Conference, from April 14 to April 16, 2004. The conference will be held in Las Vegas, Nevada (NV). (More information about the conference can be found from the website: http://www.isoneworld.org/). You plan to leave Austin on April 13, evening and return on April 17.

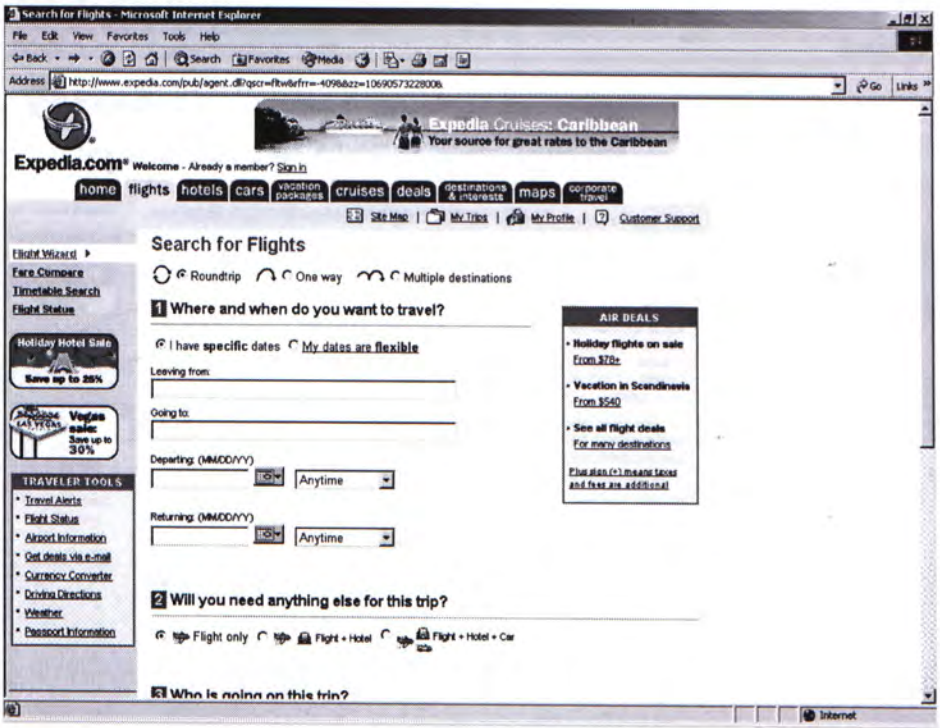
Your task is to arrange for the round trip flight and lodging for attending the conference. You plan to use the Infomediary: Expedia (http://www.expedia.com) for making the flight and lodging reservations.

Guidelines:
The instructions below will guide you through the information gathering and purchasing process using the Infomediary, Expedia.

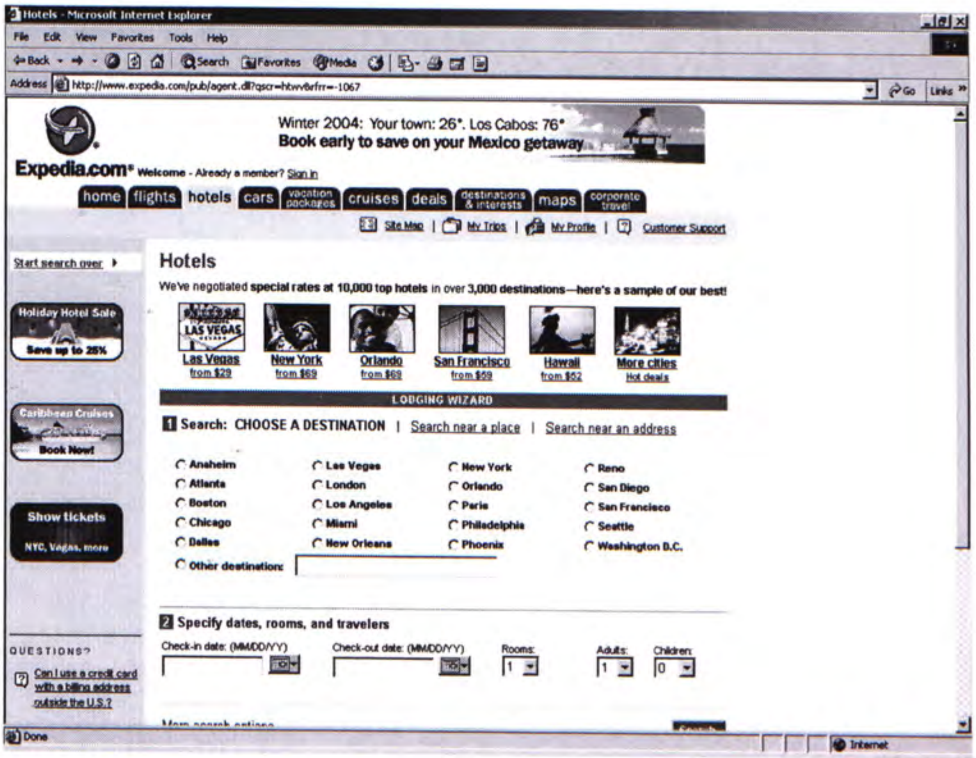
1. Go to the website: Expedia (http://www.expedia.com/).



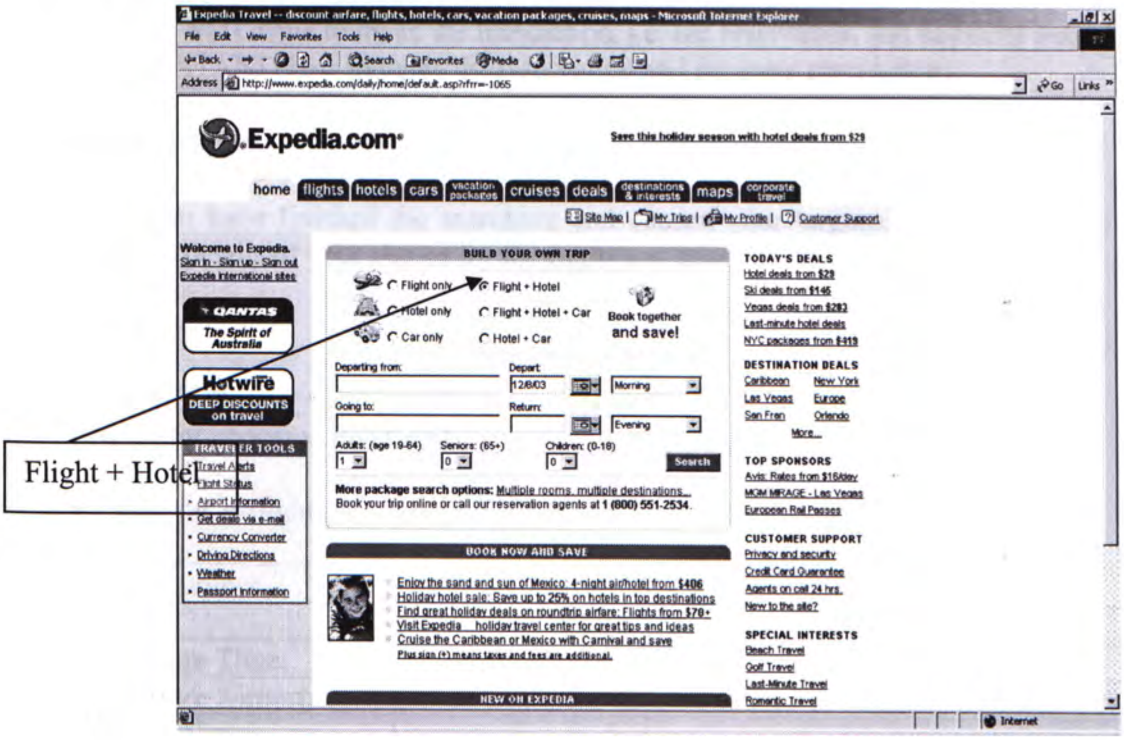
2. For flight information, you can select the "Flights" tab and then the following screen will appear. Enter details about departure city and date, destination city and date. After you submit your search, a list of flights that fit your requirements will be shown.



3. For the lounge information, you can select the "Hotels" tab and then the following screen will appear. Enter details about city, the check in and checkout date. After you submit your search, a list of hotels that fit your requirements will be shown.



4. Alternatively, you can enquire about the travel package (flights plus hotels) by selecting the button beside the "Flight + Hotel". And then enter your trip details.



5. Determine which airlines and hotels you would choose after doing the comparisons.

> **Reminder:**
> You DO NOT have to make the transaction, i.e. the reservation and payment but you need to UNDERSTAND how to make the reservation and payment transaction.

Search Results

After you have finished the searching and chosen your targeted flights and hotels, please enter the details of your choice for the flight and hotel.

Flight:

Price: USD$____________
Reason for choosing this flight:____

- Outbound flight

Flight number:	
Airline:	
Departure Time:	
Departure Airport:	
Arrival Time:	
Arrival Airport:	
Other details: (Non-stop or details of stop)	
Travel time:	

- Return flight

Flight number:	
Airline:	
Departure Time:	
Departure Airport:	
Arrival Time:	
Arrival Airport:	
Other details: (Non-stop or details of stop)	
Travel time:	

Hotel:
Reason for choosing this hotel: ______________________________________

Hotel name:	
Hotel address:	
Room details:	
Nightly rate / total rates	

Task C

Infomediary:
Yahoo Shopping

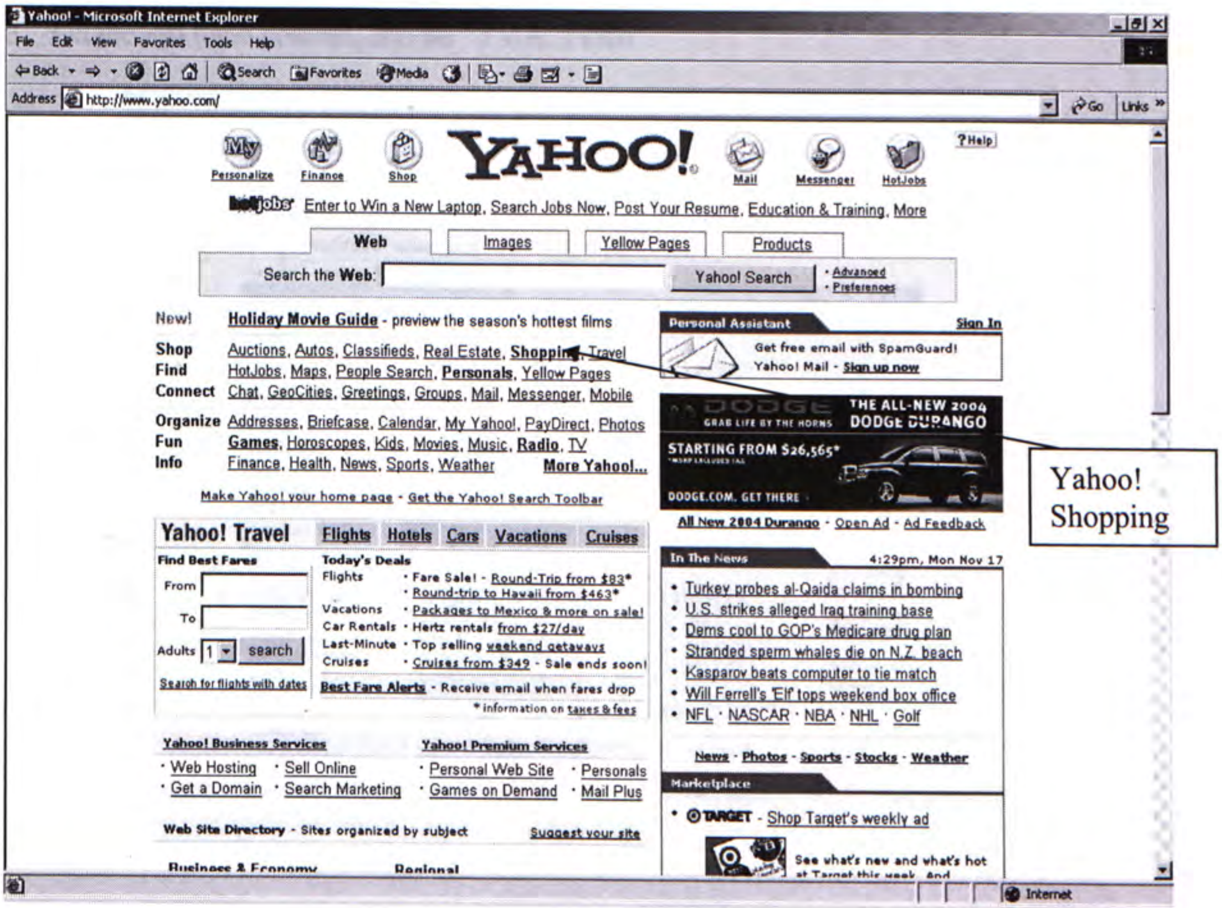
Scenario:
Assume that you want to buy a plasma TV for your new home. Your friend has recommended a model: **Samsung HPN5039,** (diagonal size: 50 inches) to you. You have little information about this model on hand now. You would now try to find out more information about this product and other alternatives with comparable price and functionality as this model. Your task is to search for a plasma TV and find out a best deal for the choice.

In brief, the specification of plasma TV you are finding:

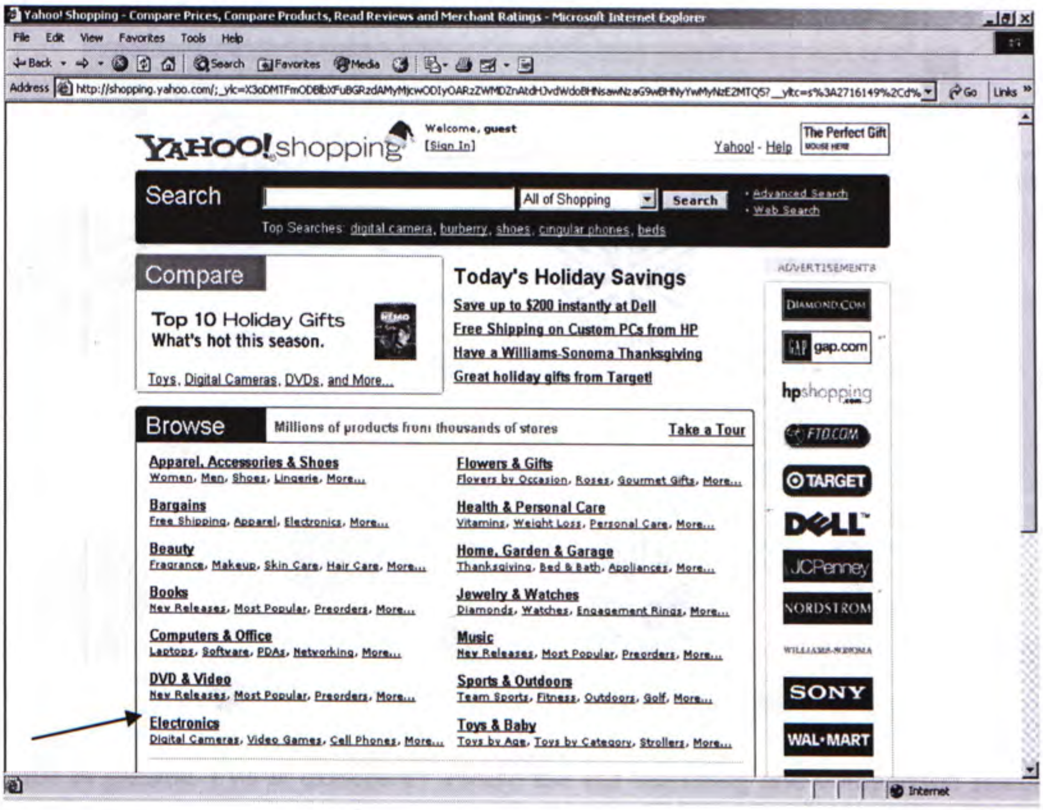
- Diagonal size of 50 inches
- Display resolution: 1366 x 768 resolution
- HDTV compatible
- Price up to $7,000

Guidelines:
The instructions below will guide you through the information gathering and purchasing process using the Infomediary, Yahoo shopping.

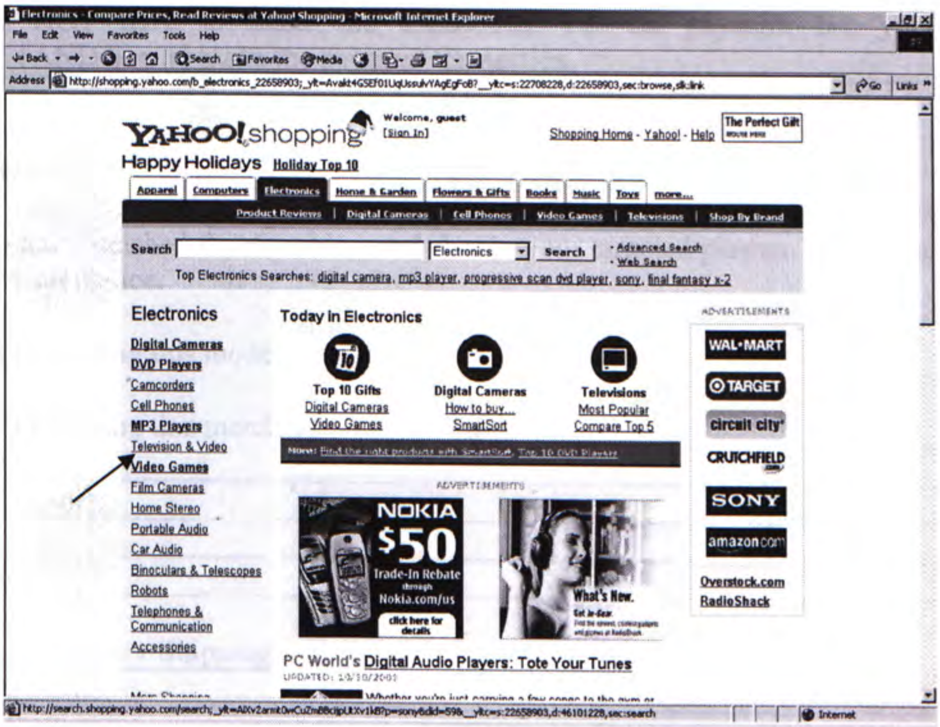
1. Go to the website: www.yahoo.com and then click on Shopping under the category: Shop



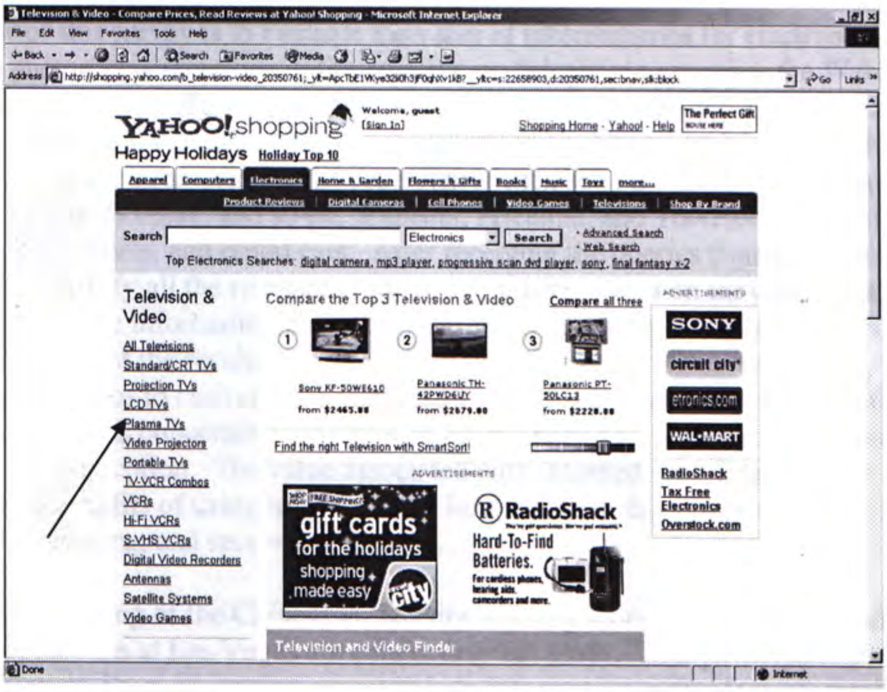
2. Choose your product category. (Plasma TV is under the category: Electronics)



3. On the left hand column, choose "TV & Video".



4. On the left hand column, choose "Plasma TV" and then search for the models that fit your requirements.



5. A list of plasma TVs is extracted. Please use the searching and comparison features of the infomediary to assist you in selecting the plasma TV that fit you the best.

Reminder:
You DO NOT have to make the transaction, i.e. the payment but you need to UNDERSTAND how to make the payment transaction.

Search Results

After you have finished the searching and chosen your targeted plasma TV, please enter the details of your choice.

Reason for choosing this model: ____________________

Reason for choosing this merchant: ____________________

Selected Model:	
Brand:	
Base Price:	
Total Price: (Base Price + Tax + Shipping)	
Merchant Name:	

MEASURING THE VALUE OF INFOMEDIARIES TO THE CUSTOMER

The purpose of this survey is to evaluate the value of infomediaries for electronic shopping based upon customer perceptions. Infomediaries are delegated to monitor the Web sites of the information providers or electronic stores and search for the most relevant information or the best products based on the customer's requirement. For example, MySimon, BizRate, and Yahoo Shopping are infomediaries for general products, such as, books, computers, electronic devices, clothing, and so on. Expedia, Priceline, and Travelocity are infomediaries for flight tickets, hotels, and rental cars. After receiving the queries from customers, the infomediaries identify all the relevant products or services based on the customers' requirements and the information they have aggregated from the potential vendors. The infomediaries present the resulted items in the order of price, vendors' reputation, the relevance of the items to customers' requirements, or weighted sum of several criteria. The survey asks questions concerning the value of infomediaries for the customers based on experience and perception. The value associated with infomediaries relates to the net value of the cost and benefits of using infomediaries for electronic shopping in terms of finding the best vendors, ordering, and receiving products.

Drs. Christopher Yang of the Chinese University of Hong Kong and Reza Torkzadeh of the University of Nevada at Las Vegas are conducting this study. Your participation with this study is voluntary. By participating, you will help information technology research at these universities. As with any research study there are risks. The risks in this study are minimal. Participants could become uncomfortable while answering some of the questions, although there are no risks expected by participating in this study. Your response will be confidential; only group data will be analysed. Respondents must be at least 18 years of age.

If you would like to receive a copy of results for this survey, please provide complete name and address on the following line:

____

For any questions, please feel free to contact the authors at the addresses below. Thank you.

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Email: rezat@unlv.edu

Respondent Information:

Name of Respondent: ______________________ Email Address: ___________________________

Name of Department: ______________________ Name of Organization: ____________________

i. Gender: ___ Male ___ Female

ii. Age: ___ Under 20 years ___ 20-29 years ___ 30-39 years ___ Over 40 years

iii. How many times per month do you shop online? _________

iv. What kind of products do you usually purchase online? _________

v. How much money do you spend for online shopping on average in a year? $_________

vi. How many electronic stores (sites) you visit before you make your purchase? _________

vii. How many times per month do you use infomediaries to assist you with your online shopping? _________

viii. How helpful are informediaries in assisting you to identify the best products with the best price?

1 Not at all	2 A little	3 Moderately	4 Much	5 A great deal

The following questions relate to **issues** that influence your decision to use infomediaries for electronic shopping. In answering these questions, think about your engagement experiences with infomediaries and circle the response that best describes your belief using the following scale.

1 Not at all	2 A little	3 Moderately	4 Much	5 A great deal

1. I like to see increased fraud prevention for infomediaries.	1 2 3 4 5
2. I am concerned about fraud when I want to purchase through infomediaries.	1 2 3 4 5
3. I am concerned about infomediary legitimacy.	1 2 3 4 5
4. I am concerned about how much I can trust the infomediary.	1 2 3 4 5
5. I am concerned about how much I can trust the seller suggested by the infomediary.	1 2 3 4 5
6. I feel there is sufficient transaction security built into infomediary systems.	1 2 3 4 5
7. I am concerned about security for infomediaries.	1 2 3 4 5
8. I am concerned about hackers.	1 2 3 4 5
9. I like easier search capabilities.	1 2 3 4 5
10. I am satisfied with customized profile of products through informediaries.	1 2 3 4 5
11. I am satisfied with specific information about what interests me through informediaries.	1 2 3 4 5
12. I like greater product information through infomediaries.	1 2 3 4 5
13. I like to be able to test the product.	1 2 3 4 5
14. I like to be able to try the product.	1 2 3 4 5
15. I feel the accuracy of information is important.	1 2 3 4 5

16. I am concerned about the accuracy of the product information.	1 2 3 4 5
17. I am concerned about the validity of information that I get from infomediaries.	1 2 3 4 5
18. I feel that the information that I get from informediaries is trustworthy.	1 2 3 4 5
19. I feel that the information that I get from informediaries is credible.	1 2 3 4 5
20. I feel that the information that I get from informediaries is applicable to make purchase decision.	1 2 3 4 5
21. I feel that the information that I get from informediaries is related to the purchase decision.	1 2 3 4 5
22. I feel that the information that I get from informediaries is pertinent to the purchase decision.	1 2 3 4 5
23. I feel that the information that I get from informediaries is relevant to the purchase decision.	1 2 3 4 5
24. I feel that the information that I get from informediaries is easy to comprehend.	1 2 3 4 5
25. I feel that the information that I get from informediaries is easy to read.	1 2 3 4 5
26. I feel that the good textual representation of factual information is important.	1 2 3 4 5
27. I feel that the ease to identify the product suggested by the infomediary is important.	1 2 3 4 5
28. I feel that the information that I get from informediaries is understandable to support decision to purchase.	1 2 3 4 5
29. I feel there is sufficient information through informediaries for making purchase decision.	1 2 3 4 5
30. I feel the information that I get from informediaries includes all necessary topics for making purchase decision.	1 2 3 4 5
31. I feel the information that I get from informediaries is adequate for making purchase decision.	1 2 3 4 5
32. I am concerned if the infomediary is biased on particular sellers.	1 2 3 4 5
33. I feel that the information covers a broad scope for making purchase decision.	1 2 3 4 5
34. I am concerned whether the information is updated.	1 2 3 4 5
35. I am concerned about infomediaries tracking changes in price among the sellers.	1 2 3 4 5
36. I am worried if the information is outdated.	1 2 3 4 5
37. I feel that the information is useful in making purchase decision.	1 2 3 4 5
38. I am satisfied with information gathering possibilities of infomediaries.	1 2 3 4 5
39. I am satisfied with transaction speed.	1 2 3 4 5
40. I feel that the infomediary systems are responsive to my request.	1 2 3 4 5
41. I feel that all the text and graphics are quickly loaded by the infomediary system.	1 2 3 4 5
42. I feel that the infomediary systems provide good access.	1 2 3 4 5
43. I feel that the infomediaries have simple layout for their content.	1 2 3 4 5
44. I feel that the infomediaries are easy to use.	1 2 3 4 5
45. I feel that the infomediary systems are well-organized.	1 2 3 4 5
46. I feel that the infomediary systems have clear design.	1 2 3 4 5
47. I feel that the infomediary systems are user-friendly.	1 2 3 4 5
48. I like simple user interface of the infomediaries.	1 2 3 4 5
49. I like simple systems for product searching.	1 2 3 4 5
50. I feel that the infomediary systems provide clear instruction for me to formulate the query.	1 2 3 4 5
51. I feel that the infomediaries are fun to navigate.	1 2 3 4 5
52. I feel that the infomediaries are entertaining.	1 2 3 4 5
53. I feel there is adequate number of links in infomediary systems.	1 2 3 4 5
54. I feel that the descriptions for each links on infomediaries are clear.	1 2 3 4 5

55. I feel that it is easy to go back and forth between pages of the infomediary.	1 2 3 4 5
56. I feel that the infomediaries are easy to navigate.	1 2 3 4 5
57. I like to see the capability of creating a list of selected items by the infomediary.	1 2 3 4 5
58. I like to see the capability of creating a customized product by the infomediary.	1 2 3 4 5
59. I like to see the capability of selecting different features of the product to match my needs.	1 2 3 4 5
60. I like to participate in creating my desired product together with the infomediary.	1 2 3 4 5
61. I like to be able to modify my queries for Infomediaries.	1 2 3 4 5
62. I am concerned about the customized information provided by the infomediary.	1 2 3 4 5
63. I like the possibility of comparison-shopping.	1 2 3 4 5
64. I like to enhance comparison-shopping.	1 2 3 4 5
65. I like the ease of comparison-shopping.	1 2 3 4 5
66. I feel that the infomediaries is helping me in making better purchase decisions.	1 2 3 4 5
67. I like having maximum product variety.	1 2 3 4 5
68. I like to have greater product choice.	1 2 3 4 5
69. I like to have greater product selection.	1 2 3 4 5
70. I like to have maximum range of quality product options.	1 2 3 4 5
71. I like to have quick response from the infomediary system.	1 2 3 4 5
72. I feel that the infomediaries response promptly.	1 2 3 4 5
73. I am concerned about misuse of my credit card.	1 2 3 4 5
74. I am worried about who will have access to my credit card number.	1 2 3 4 5
75. I am concerned about unauthorized use of my credit card.	1 2 3 4 5
76. I am concerned about misuse of my personal information.	1 2 3 4 5
77. I am concerned about receiving unsolicited material.	1 2 3 4 5
78. I am concerned about receiving junk email.	1 2 3 4 5
79. I am concerned about my personal information being shared.	1 2 3 4 5
80. I am concerned about transaction error.	1 2 3 4 5
81. I worry about being charged inaccurately.	1 2 3 4 5
82. I am concerned about charging errors.	1 2 3 4 5
83. I am concerned about shipping errors.	1 2 3 4 5
84. I am concerned I might purchase more than I need to.	1 2 3 4 5
85. I am concerned about impulsive buying.	1 2 3 4 5
86. I am concerned about unnecessary purchase.	1 2 3 4 5
87. I worry about reliable delivery.	1 2 3 4 5
88. I am concerned about timely delivery of purchased items.	1 2 3 4 5
89. I like assurance for arrival of purchased product.	1 2 3 4 5
90. I like to travel as little as possible to purchase.	1 2 3 4 5
91. I like to drive as little as possible to shop.	1 2 3 4 5
92. I feel that human customer support is important.	1 2 3 4 5
93. I feel there should be opportunity for personal interaction.	1 2 3 4 5
94. I am satisfied with computer-based customer support alone.	1 2 3 4 5
95. I like to be able to talk with a salesperson.	1 2 3 4 5
96. I feel that computer-based customer support is sufficient.	1 2 3 4 5

The following questions relate to your **objectives** when using infomediaries. In answering these questions, think about your engagement experiences with infomediaries and circle the response that best describes your belief using the following scale.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly Agree

97. It is important to maximize convenience.	1 2 3 4 5
98. It is important to maximize purchasing convenience.	1 2 3 4 5
99. It is important to minimize time pressure when shopping.	1 2 3 4 5
100. It is important to provide quality after-sale service.	1 2 3 4 5
101. It is important to assure an easy return process.	1 2 3 4 5
102. It is important to minimize effort of shopping.	1 2 3 4 5
103. It is important to make shopping easy.	1 2 3 4 5
104. It is important to minimize personal hassle.	1 2 3 4 5
105. It is important to maximize ease of finding product.	1 2 3 4 5
106. It is important to minimize processing time.	1 2 3 4 5
107. It is important to minimize payment time.	1 2 3 4 5
108. It is important to minimize queuing time.	1 2 3 4 5
109. It is important to minimize waiting time.	1 2 3 4 5
110. It is important to minimize time to find product.	1 2 3 4 5
111. It is important to minimize search time.	1 2 3 4 5
112. It is important to minimize time to order product.	1 2 3 4 5
113. It is important to minimize time to select a product.	1 2 3 4 5
114. It is important to minimize product cost.	1 2 3 4 5
115. It is important to minimize tax cost.	1 2 3 4 5
116. It is important to minimize shipping cost.	1 2 3 4 5
117. It is important to maximize privacy.	1 2 3 4 5
118. It is important to avoid getting on electronic mailing lists.	1 2 3 4 5
119. It is important to make shopping a social event.	1 2 3 4 5
120. It is important to minimize worry of shopping.	1 2 3 4 5
121. It is important to inspire customers.	1 2 3 4 5
122. It is important to give customer new ideas.	1 2 3 4 5
123. It is important to minimize regret of shopping.	1 2 3 4 5
124. It is important to minimize regret of shopping online.	1 2 3 4 5
125. It is important to minimize online shopping disappointment.	1 2 3 4 5
126. It is important to maximize customer confidence.	1 2 3 4 5
127. It is important to minimize shopping effort.	1 2 3 4 5
128. It is important to maximize safe shopping experience.	1 2 3 4 5
129. It is important to maximize product value.	1 2 3 4 5
130. It is important to ensure quality of product.	1 2 3 4 5
131. It is important to get the best product for the buck.	1 2 3 4 5
132. It is important to minimize time to receive product.	1 2 3 4 5

133. It is important to minimize delivery time.	1 2 3 4 5
134. It is important to minimize shipping time.	1 2 3 4 5
135. It is important to minimize risk of product use.	1 2 3 4 5
136. It is important to minimize environmental impact.	1 2 3 4 5
137. It is important to reduce environmental damages.	1 2 3 4 5
138. It is important to minimize pollution.	1 2 3 4 5

Appendix E

Tutorial Guide for experiment on Collaborative Infomediary

TUTORIAL GUIDE for the Experiment on Collaborative Infomediary

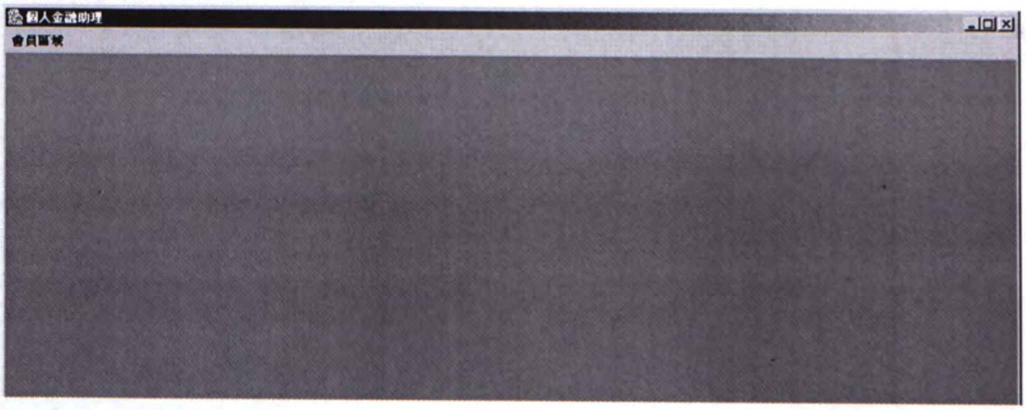
Introduction

The purpose of this experiment is to evaluate the system performance of the "Collaborative agent" of the Personal Financial Agent. It is an intelligent agent that helps users to search for Chinese Financial Information post on web. This experiment asks you to provide feedback on the news articles you read.

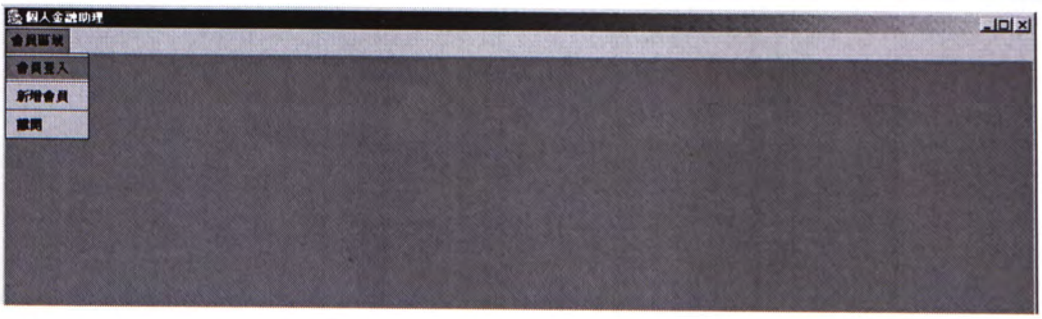
Tutorial Session

1. User Login (會員登入)

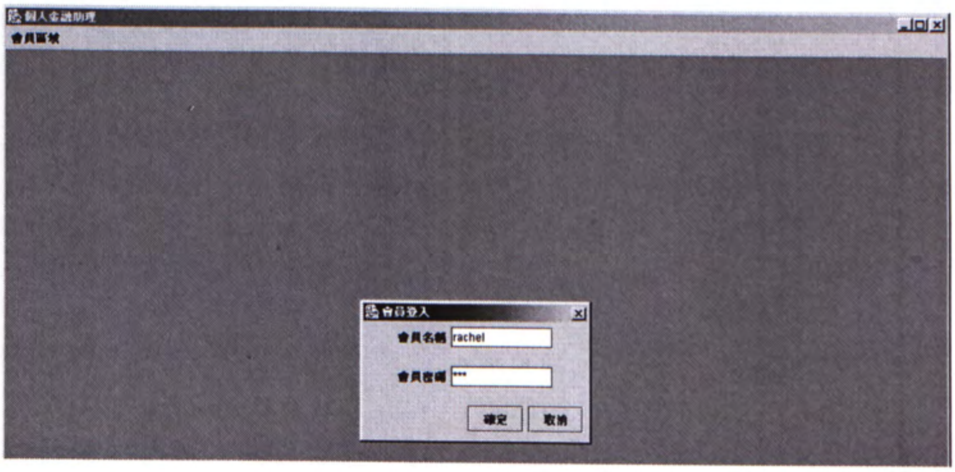
On the menu path, you will see the option “會員區域”.



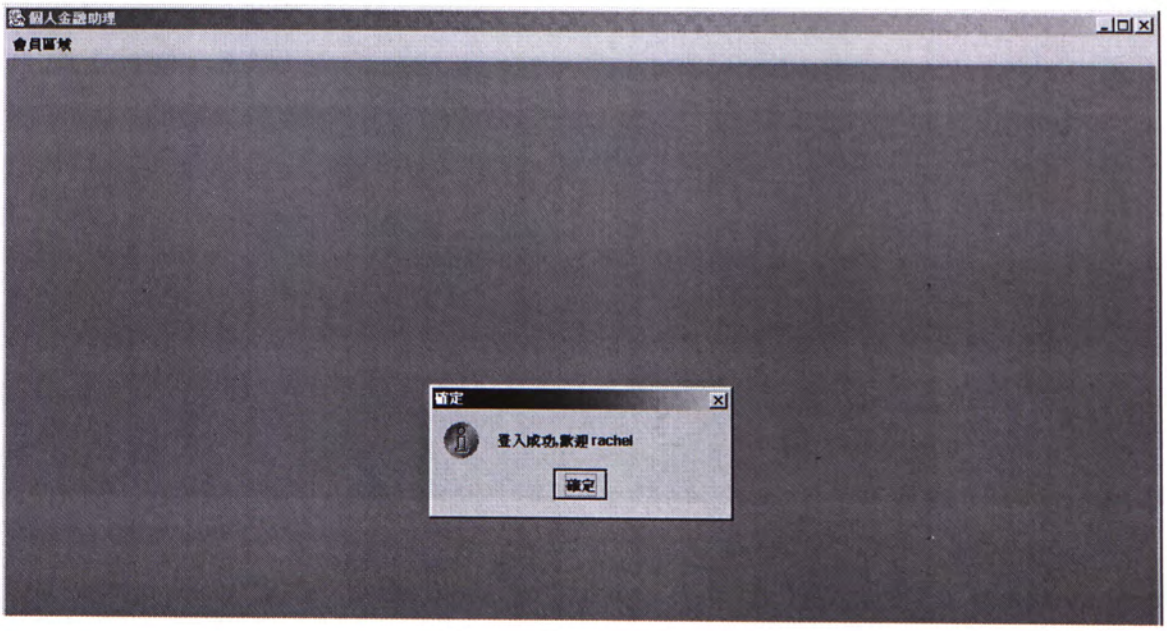
In order to login to use the system, you left click on this option and there are three options in the pull down menu.



You can left click on “會員登入” and the following dialog box will prompt out. You can enter your username and password in the fields “會員名稱” and “會員密碼” respectively, and left click on the “確定” button to confirm the login.

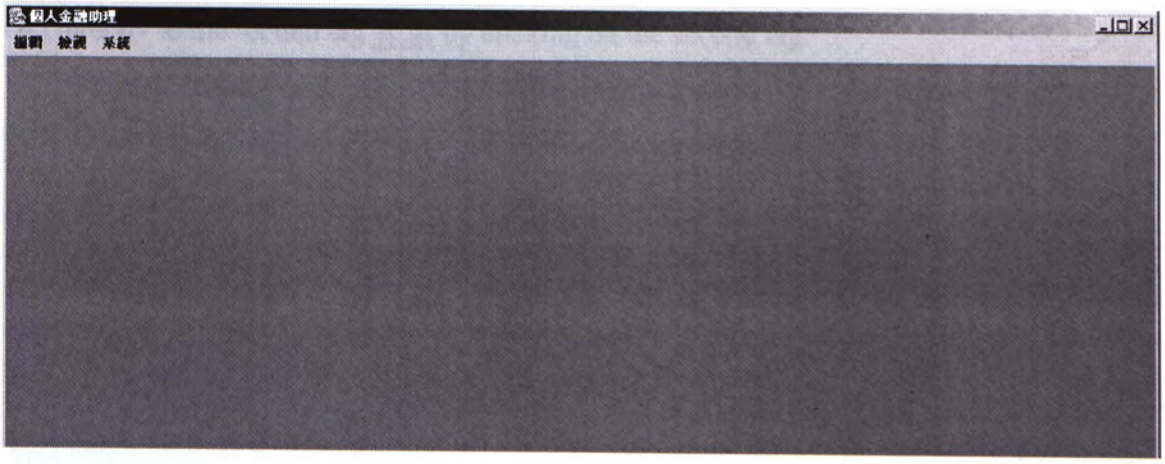


After you hit the "the "確定" button, the following message box will prompt out and you hit 確定" button to discharge the message.



2. User Profile Configuration (個人設定)

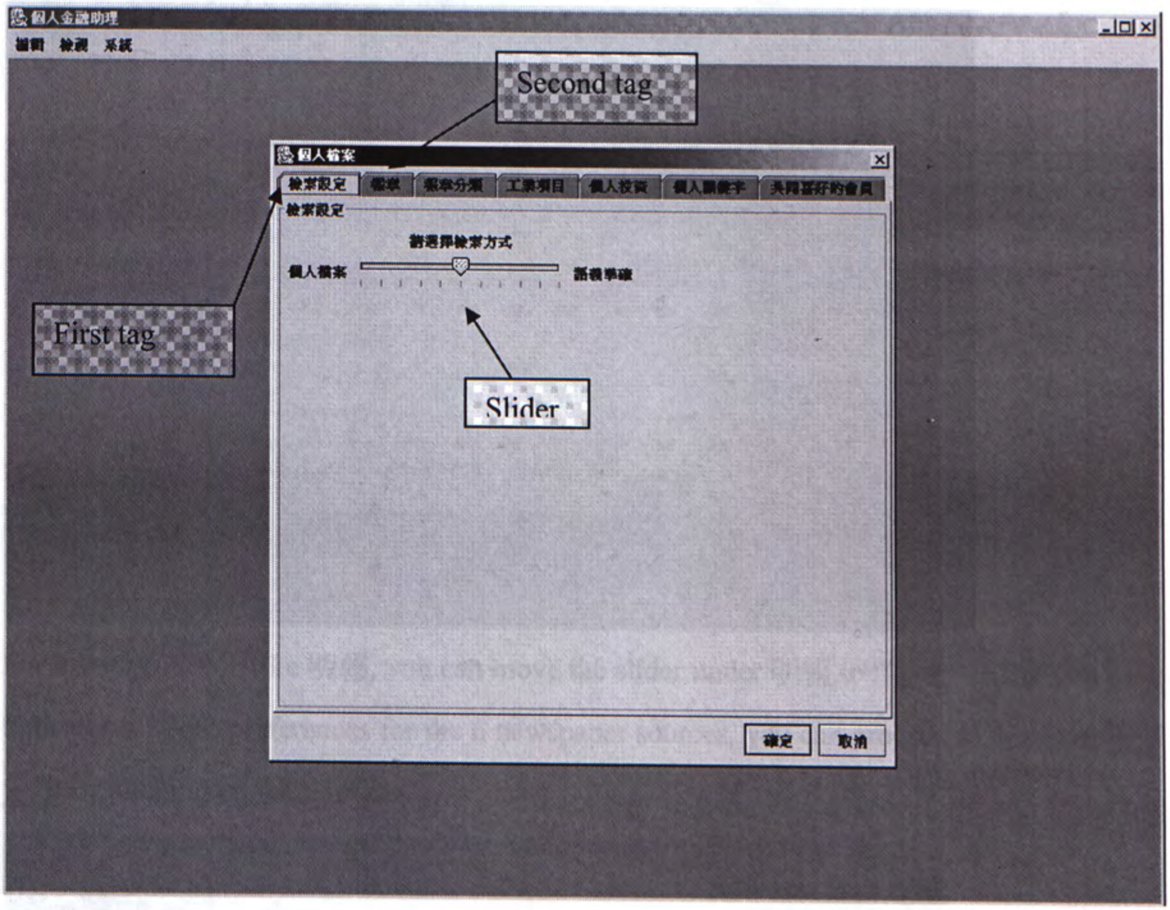
After you have successfully login, the following screen appears with three options in the menu bar.



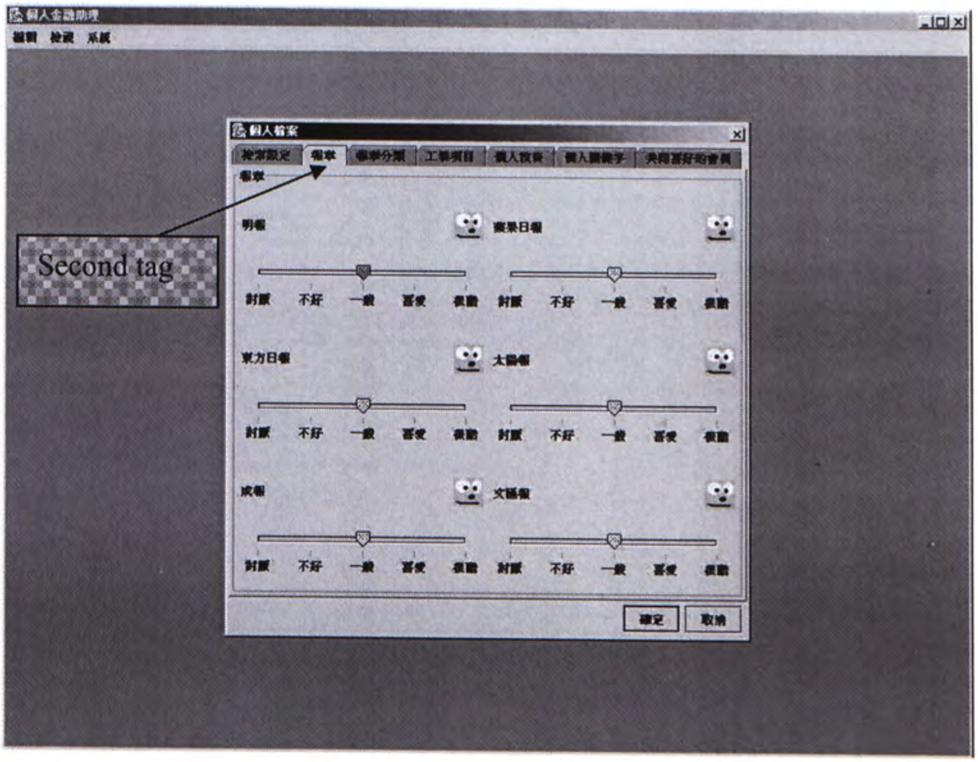
You have to select "編輯" in the menu bar and then click on "個人設定" to customize your personal profile. (The user profile setting 個人設定 dialog box will automatically prompt out after you first login to the system.)

After you click on "個人設定", the following dialog box prompts out. There are 7 tags in the dialog box. Please **DO NOT** move the slider in the first tag, "檢索設定", it is default in the mid point.

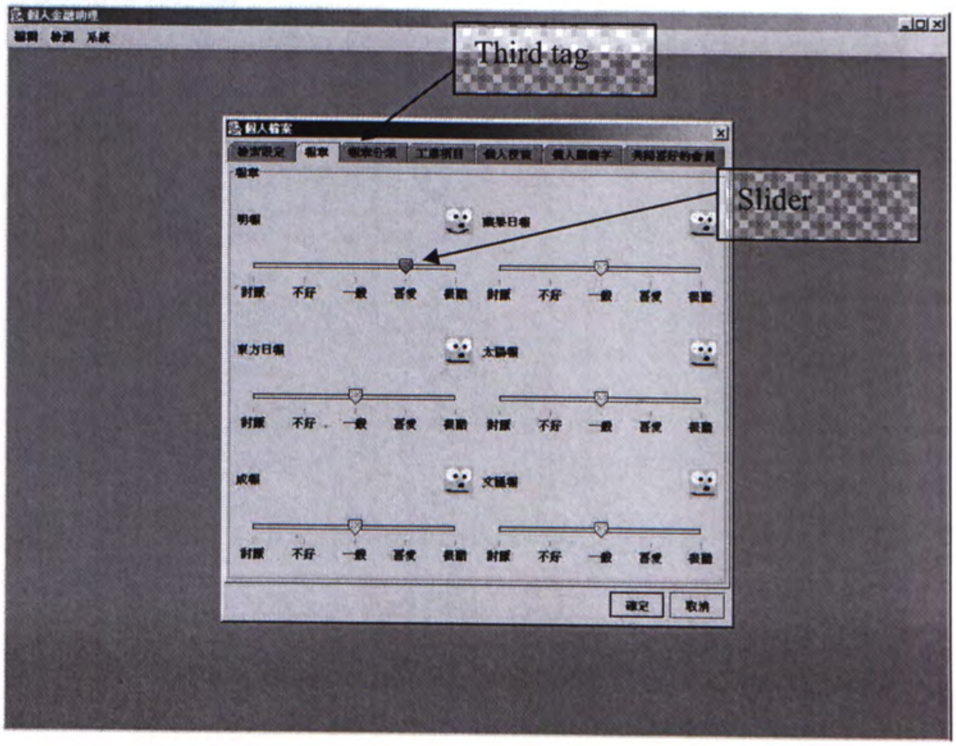
GO directly to the second tag 報章 by clicking on the second tag.



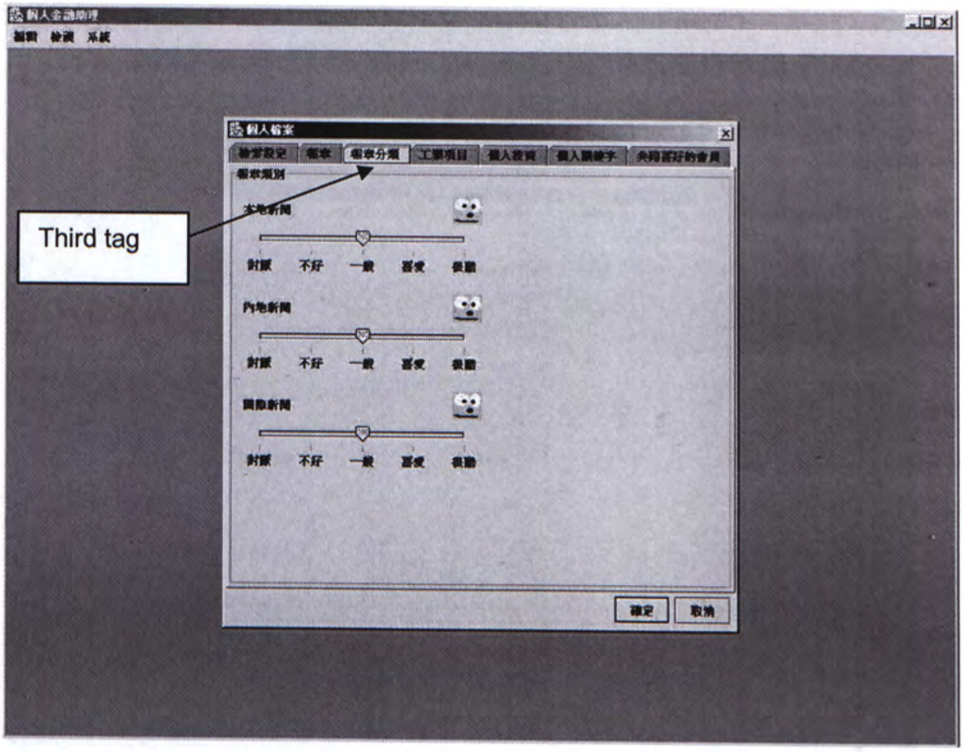
In the second tag "報章", there are six online newspaper sources, you can indicate your preferences by moving the slider for each individual newspaper source.



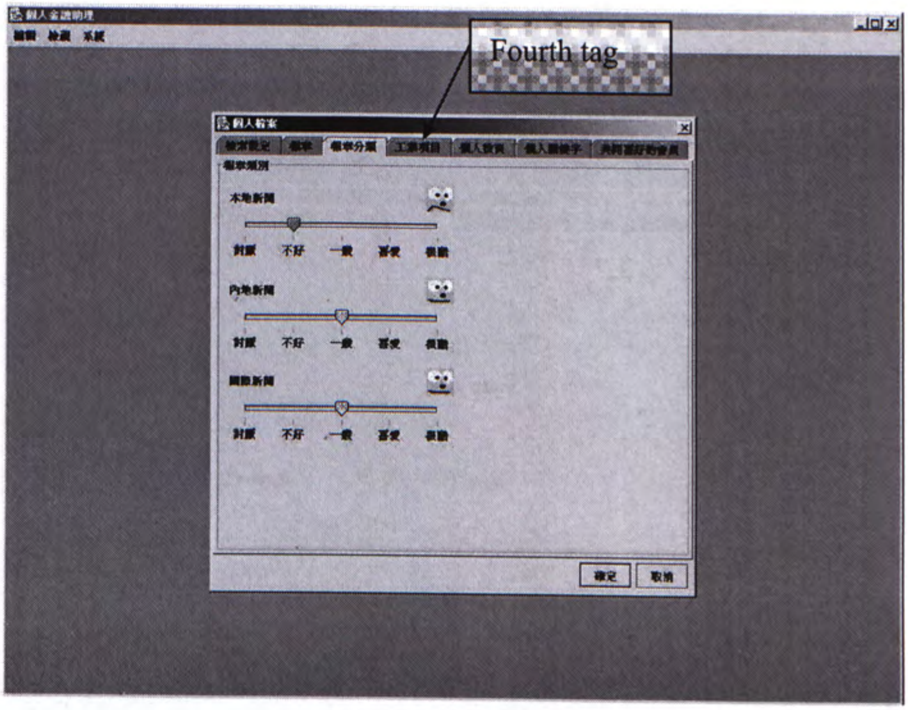
For instance, if you like 明報, you can move the slider under 明報 to "喜愛". After you have indicated all your preferences for the 6 newspaper sources, you can proceed to third tag <u>報章分類</u> by clicking on the third tag.



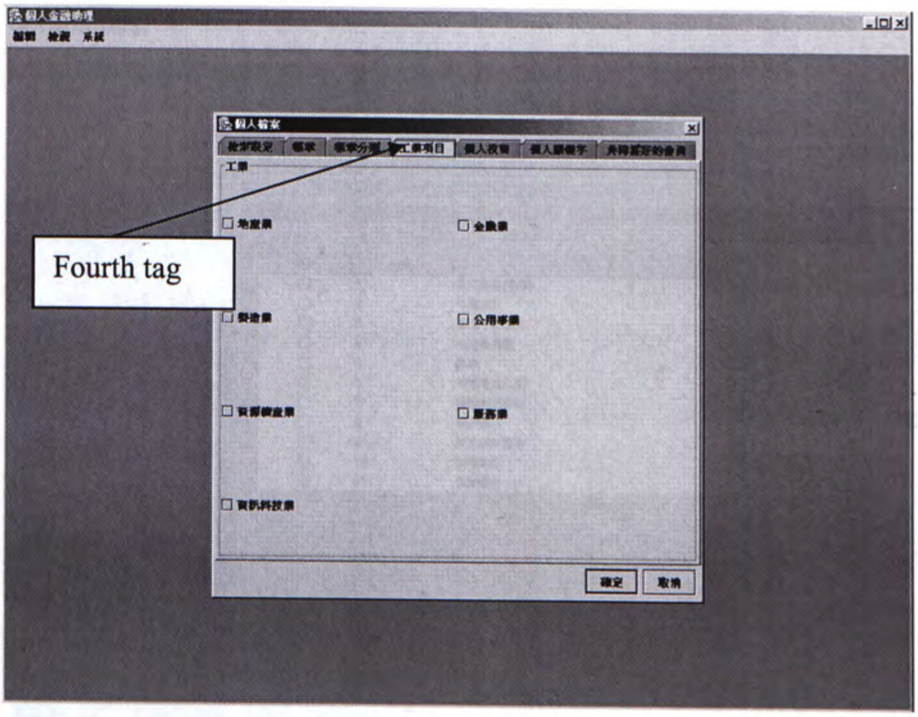
In the third tag, - 報章分類, again, you can move the slider to indicate your preference to the types of news articles you preferred. There are 3 regions of news, 本地, 內地, and 國際.



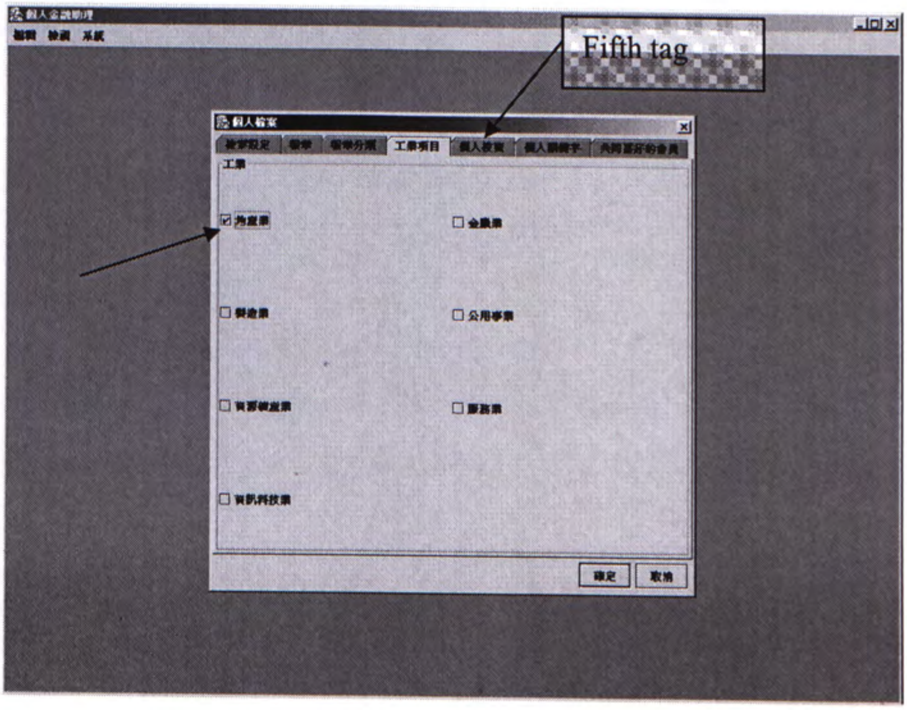
For example, if you do not like local news, 本地新聞, you can move the slider to 不好. After you have indicated all your preferences for the 3 news regions, you can proceed to the fourth tag 工業項目 by clicking on the fourth tag



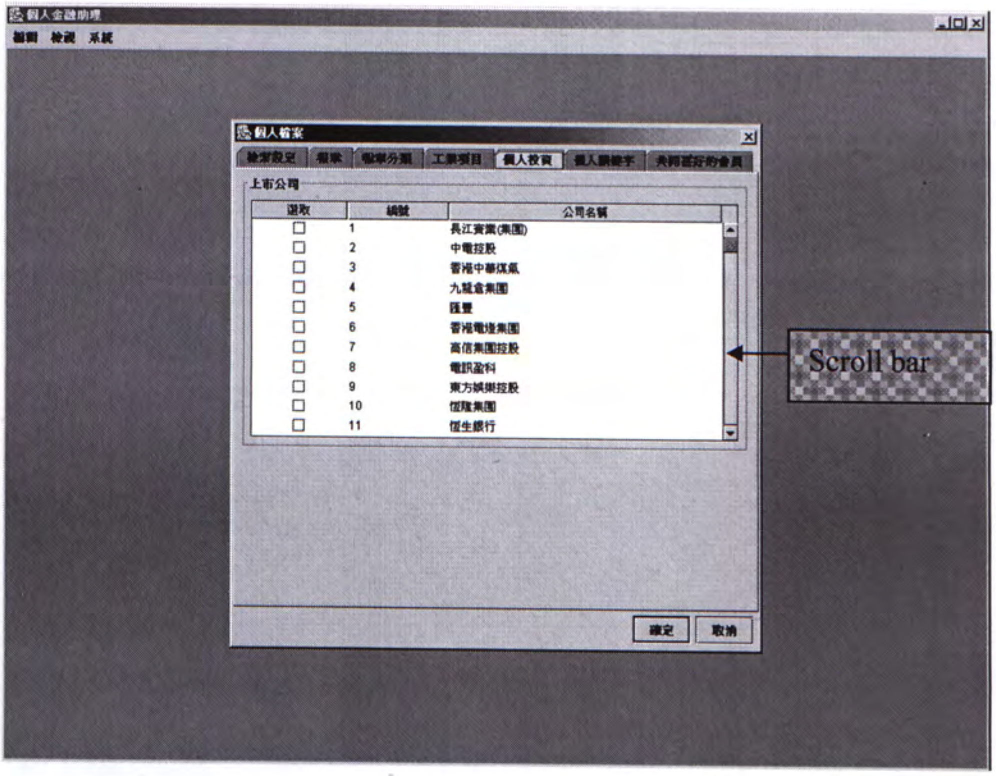
In the fourth tag - 工業項目, there are 7 categories of industry in which news articles are classified to, you can select the industries you preferred by clicking the box besides the industry name.



For instance, if I like real estate, I click on the box beside 地產業. You will see there is a "tick" mark in the box beside 地產業 after I selected it. After you have indicated all your preferences for the 7 industries, you can proceed to the fifth tag 個人投資 by clicking on the fifth tag.

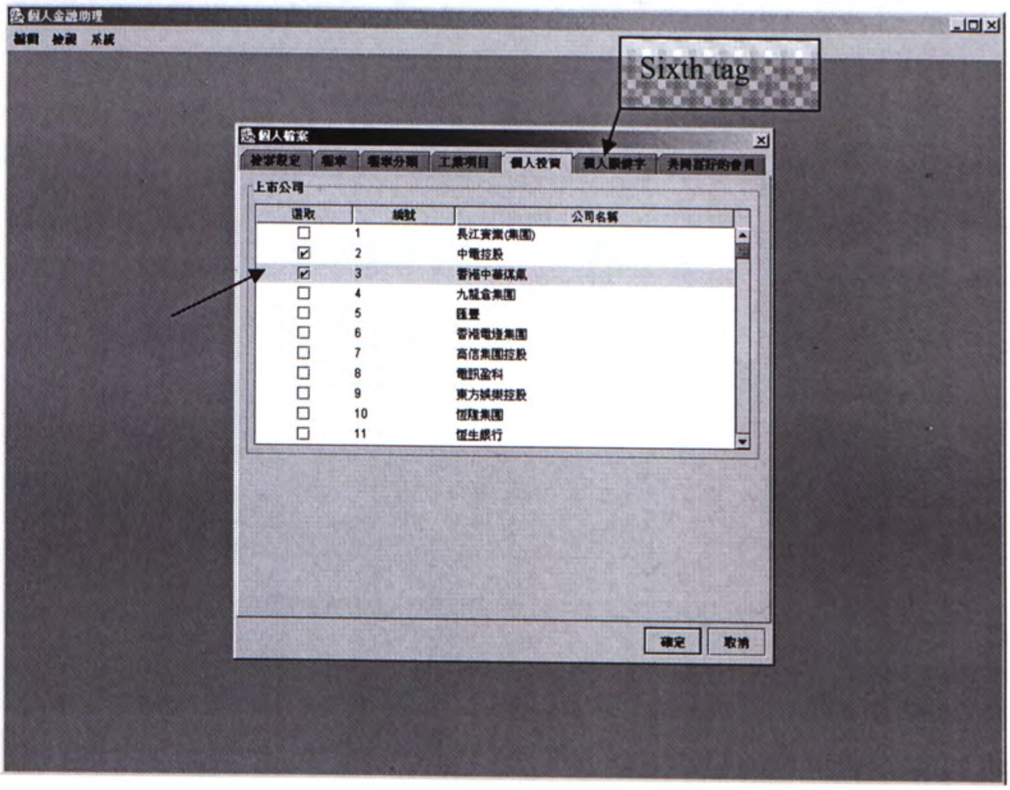


In the fifth tag - 個人投資, you can see the list of company names and their corresponding codes in the Hong Kong exchange. Again, you can choose you preferred company by clicking on the box beside the company code. You can scroll down to view all the listed companies.

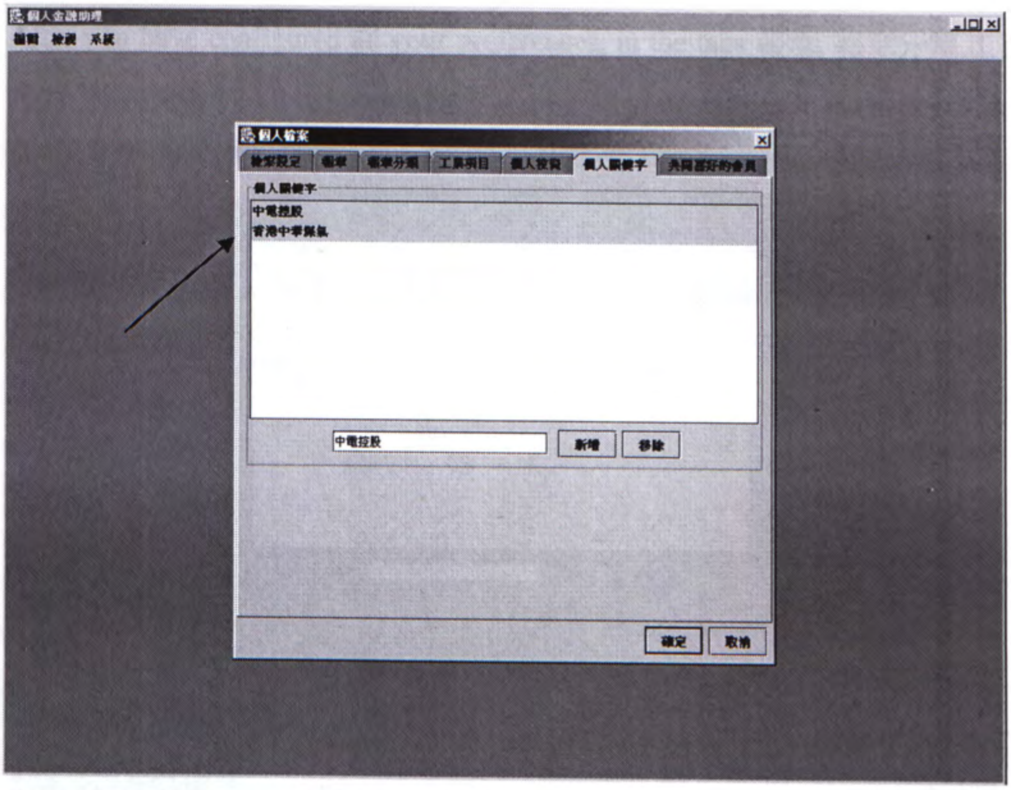


For example, if I want to choose the companies “中電控股” and “香港中華煤氣”, I click on the two boxes. After that, there will be “tick” mark in the boxes.

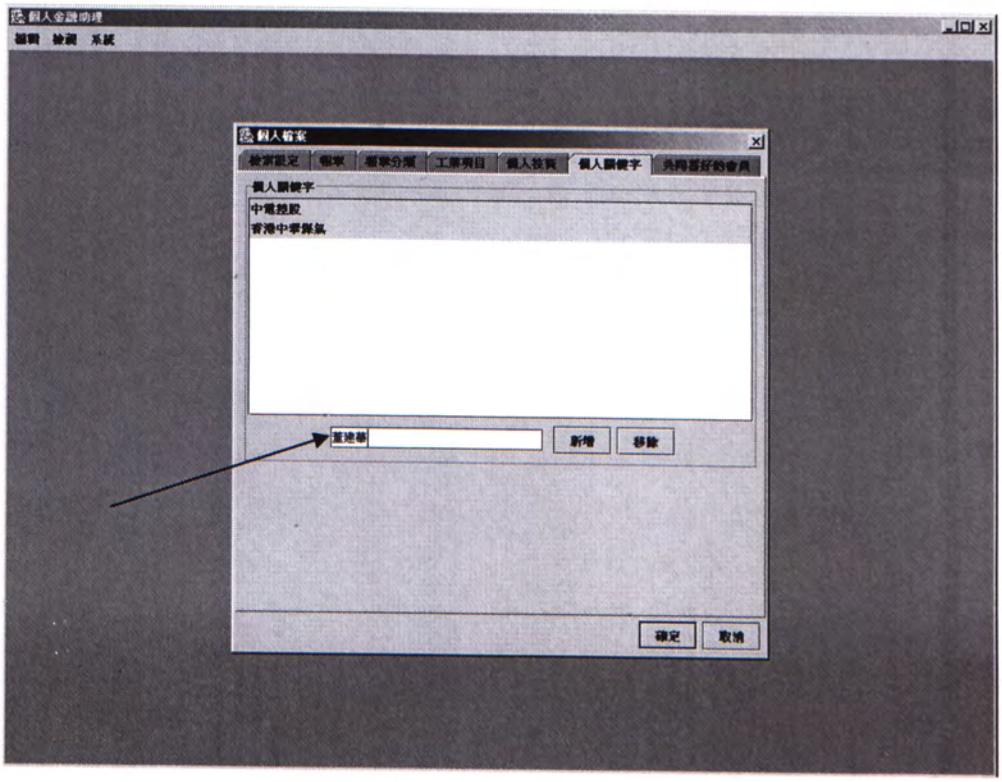
After you have chosen the listed companies, you can proceed to the sixth tag <u>個人關鍵字</u> by clicking on the sixth tag.



In the sixth tag - 個人關鍵字, by default, the name of the companies you have selected in the previous tag will be shown. You can specify keywords other than the predefined companies' name.

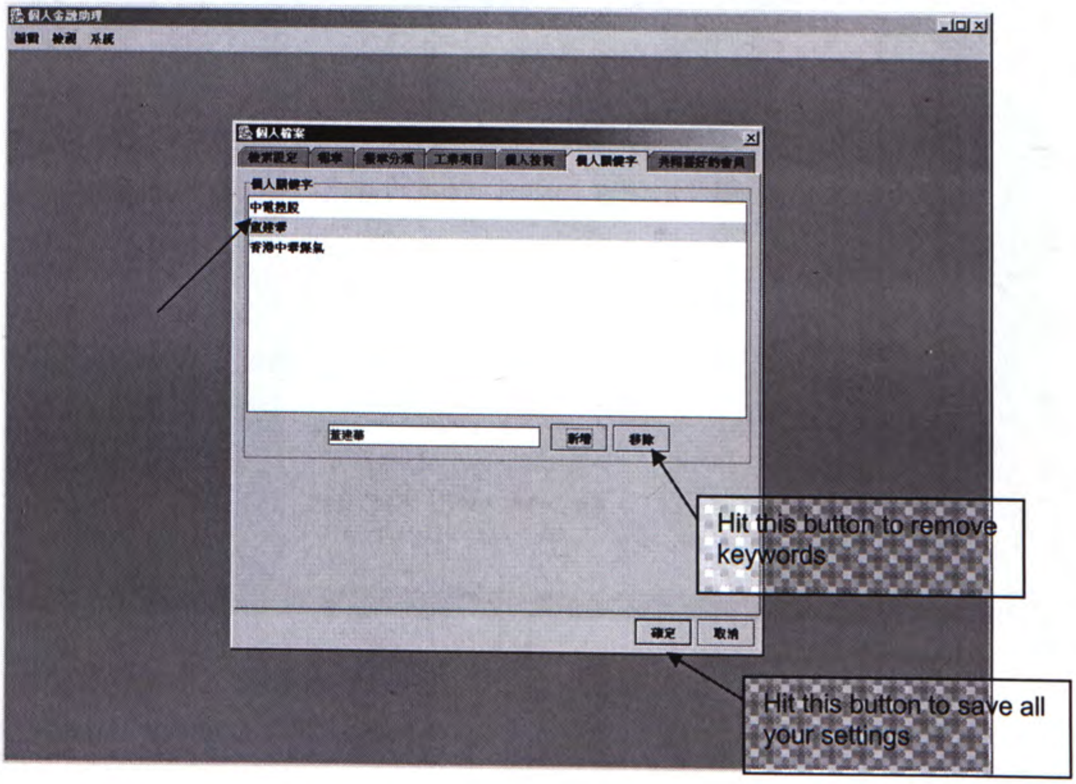


You can type in keywords in the white box. For instance, I want to have some news related to 董建華, I type in his name in the white box.

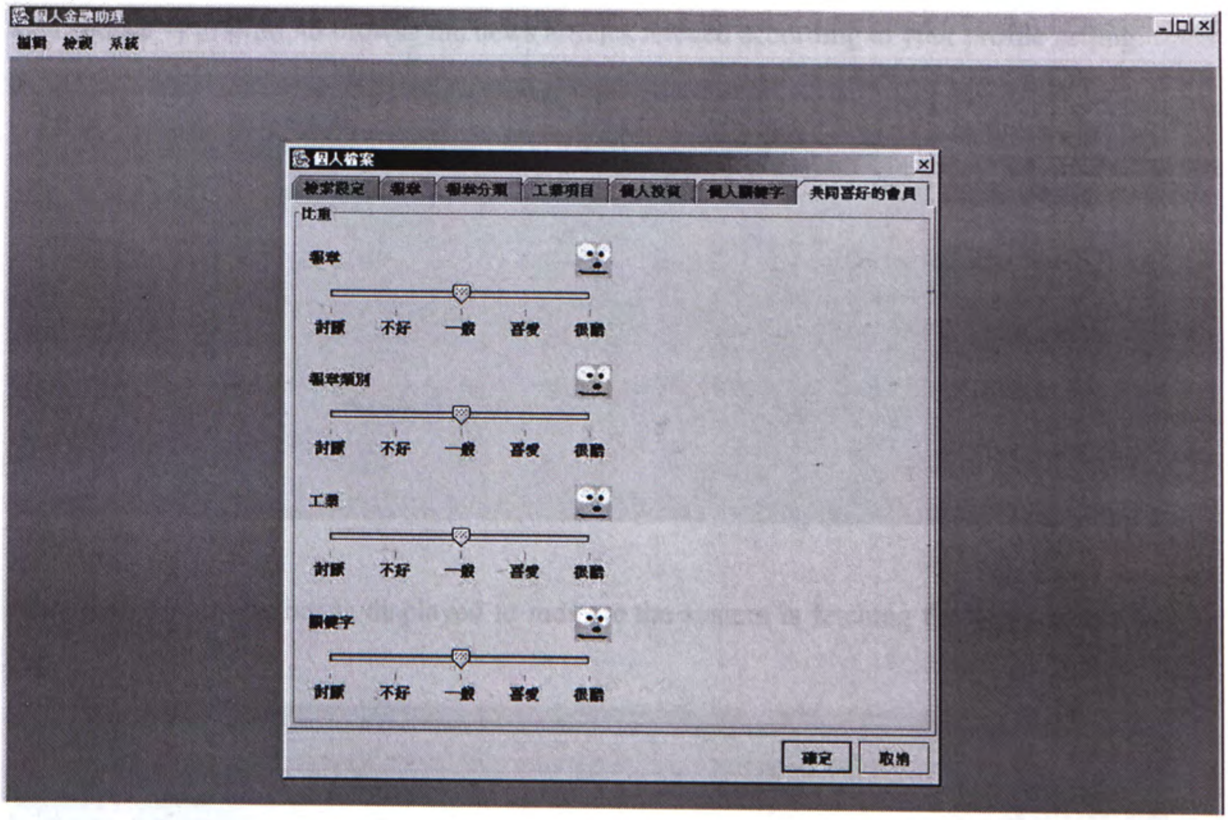


After that, I click the button "新增", the words will be added and appeared the big white box under 個人關鍵字. You can also remove keywords by highlighting on the keywords and then hit 移除.

After you have configured all your preferences, in the tags 報章, 報章分類,工業項目, 個人投資, 個人關鍵字, hit the button 確定 to save all your settings in the user profile.

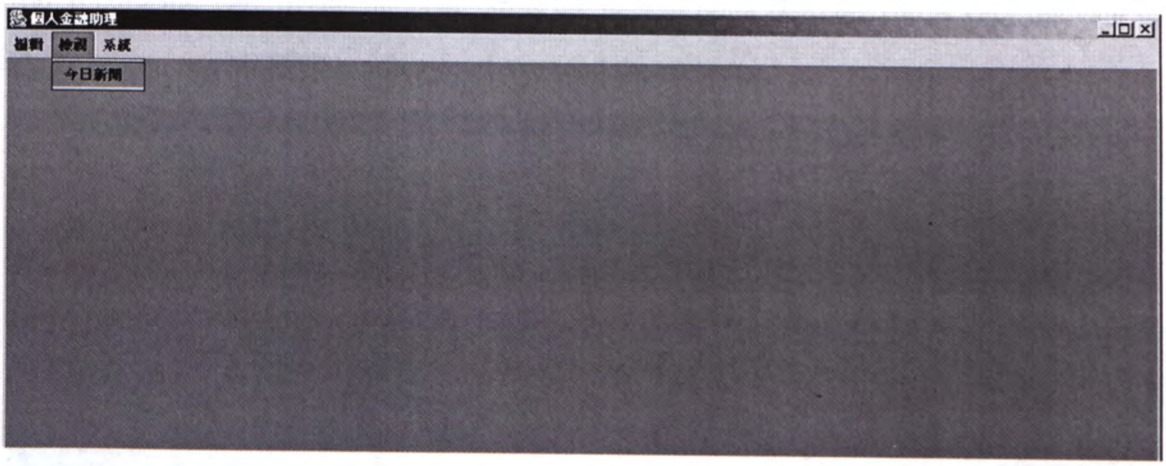


Please ignore the last tag - 共同喜好的會員. DO NOT move the sliders in it.

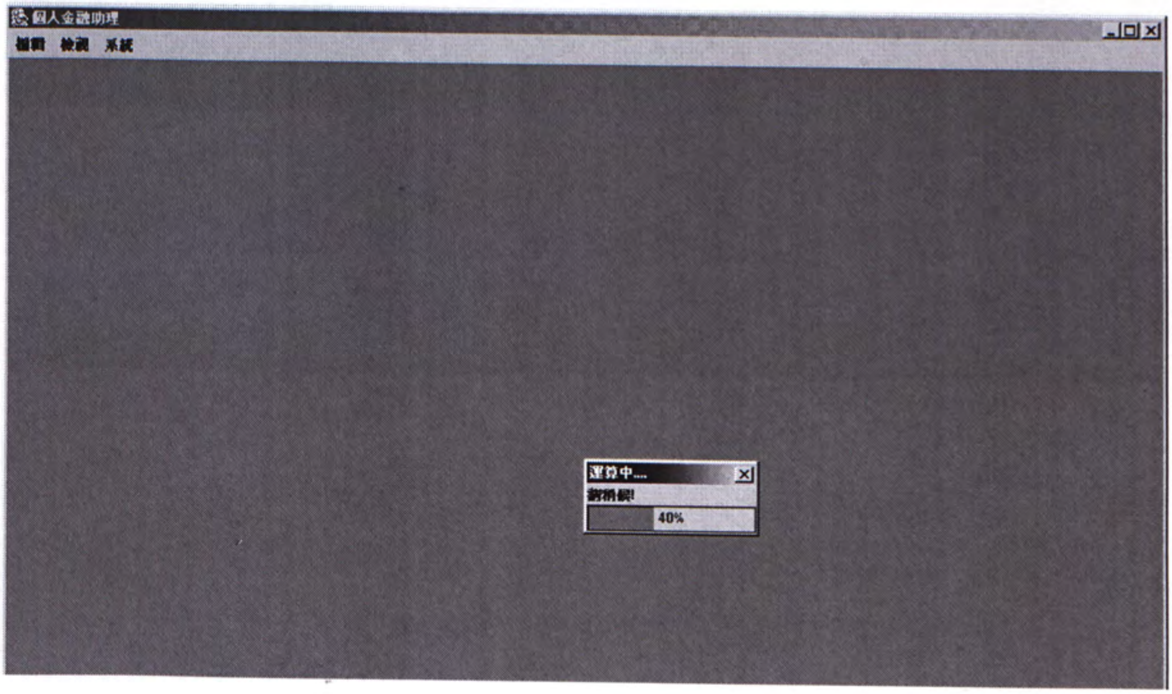


3. News Browsing (新聞檢視)

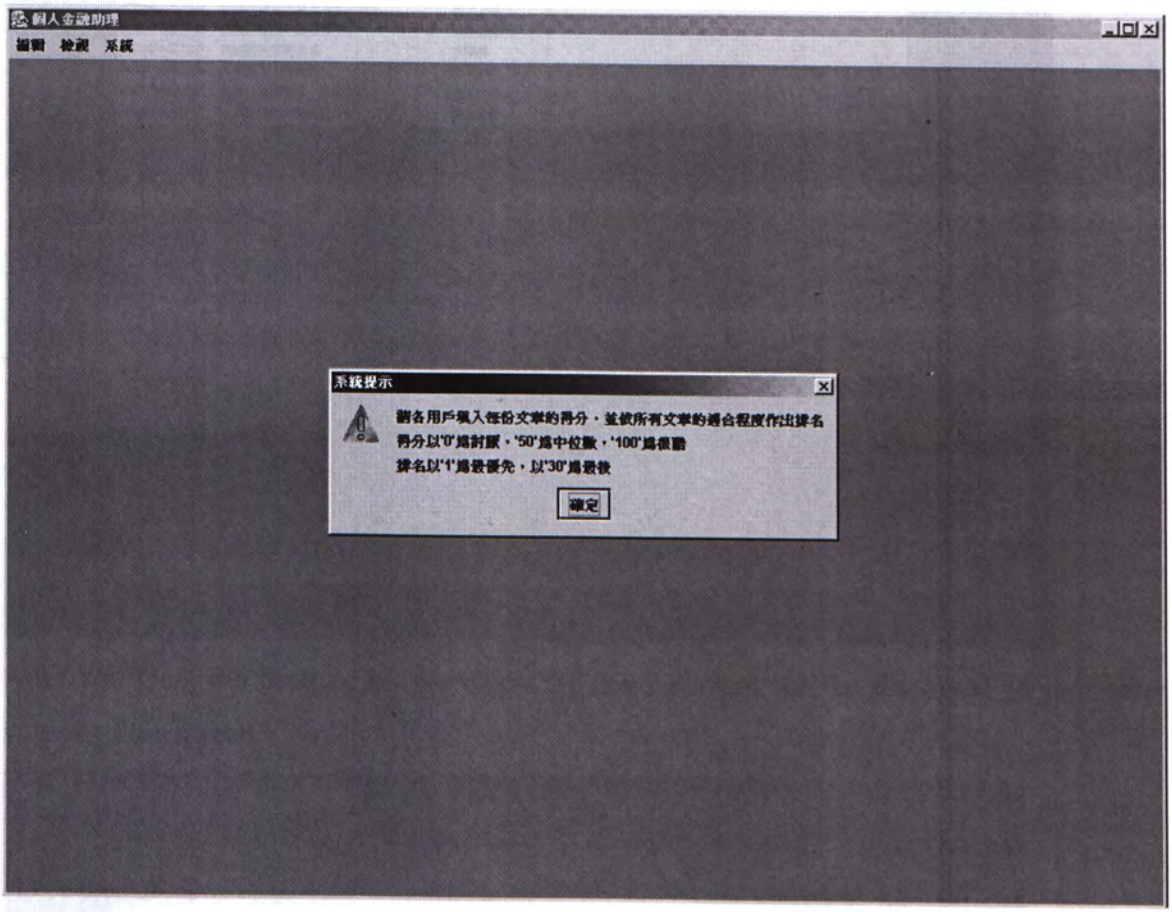
After you have saved the user profile setting, you choose the option 檢視 in the menu bar and then choose 今日新聞, to browse the news articles fetched according to your profile setting.



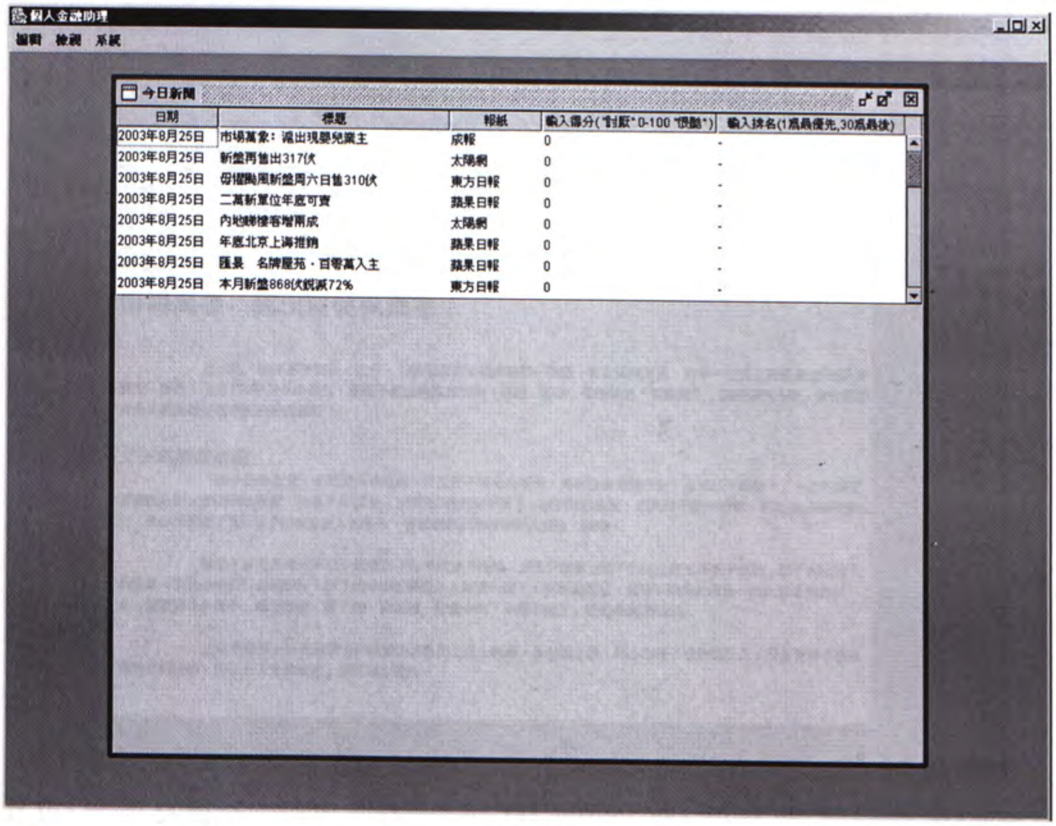
After that, a progress bar is displayed to indicate the system is fetching the news article for you.



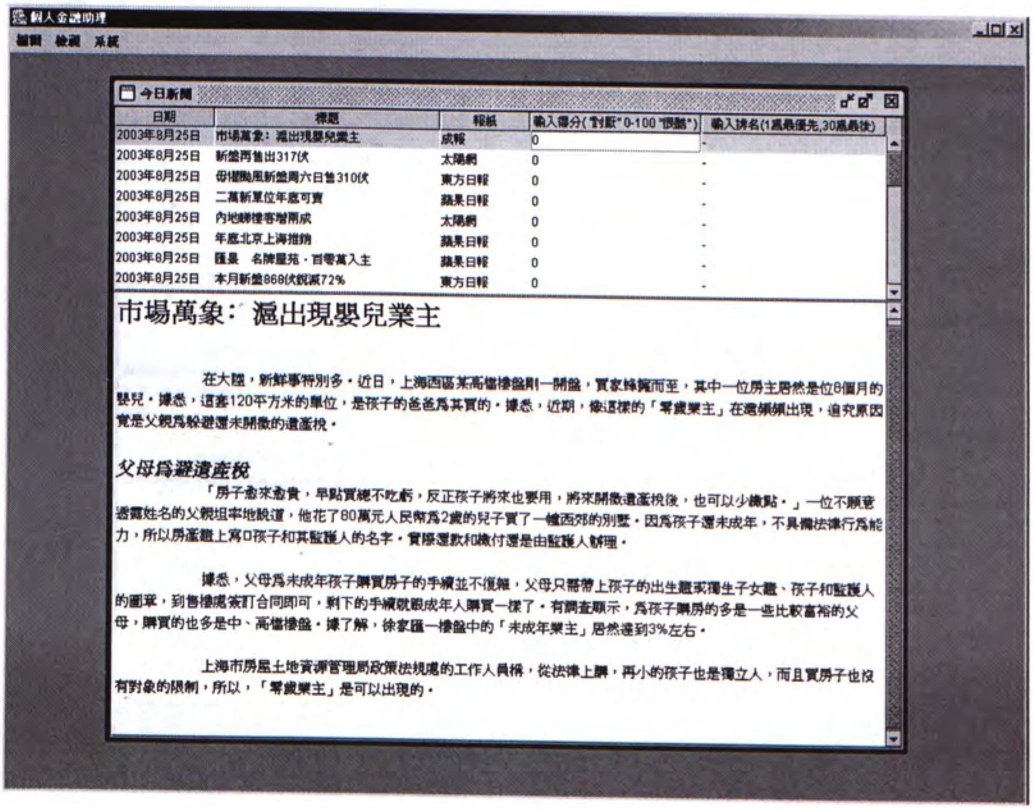
After all news articles are fetched, the following message box prompt out, it reminds you to provide a ranking of the news article fetched. Please note that "1" is the most relevant. The message also reminds you that you have to input the ratings for the news article, from 0 to 100. 0 indicates very irrelevant 討厭, 50 is the neutral point 中位數, 100 is very relevant 很酷. Then you can hit 確定 to after you have read the message.



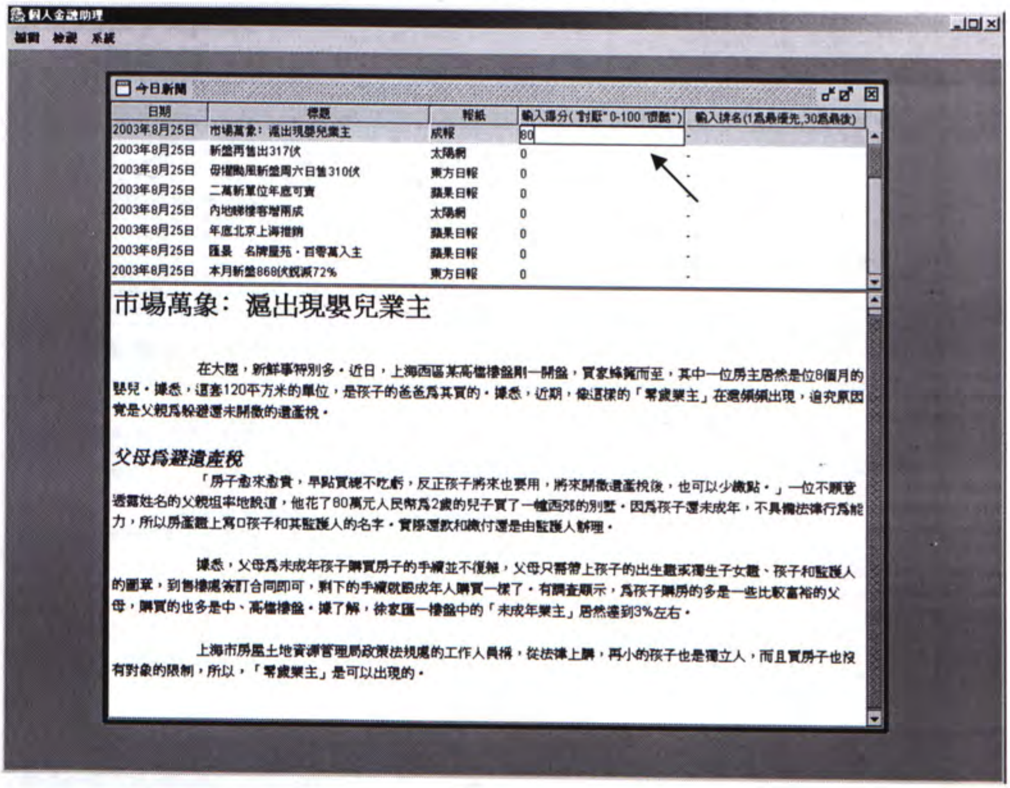
You can click or the news article to browse on it. You have to input your ratings under the column 輸入得分 and input the ranking in 輸入排名 column.



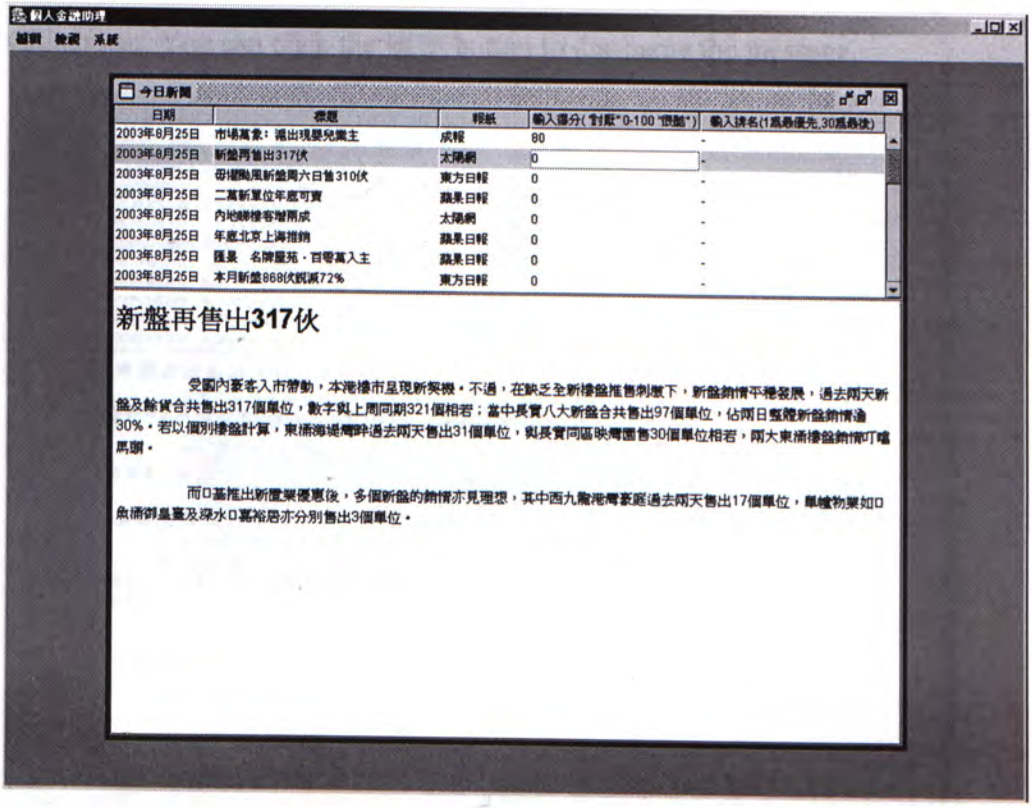
After you click the heading on the news, the news content will be displayed on the lower section of the screen.



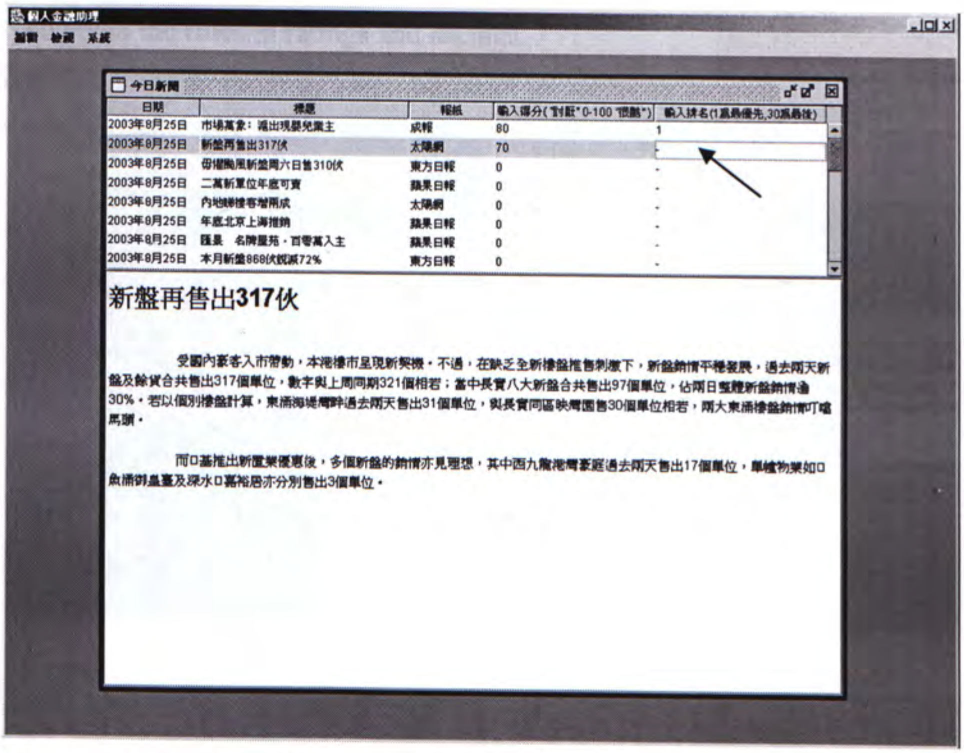
After you have read the news, you can input the ratings under the column 輸入得分. You hit "enter" key on the keyboard to confirm you rating on this article.



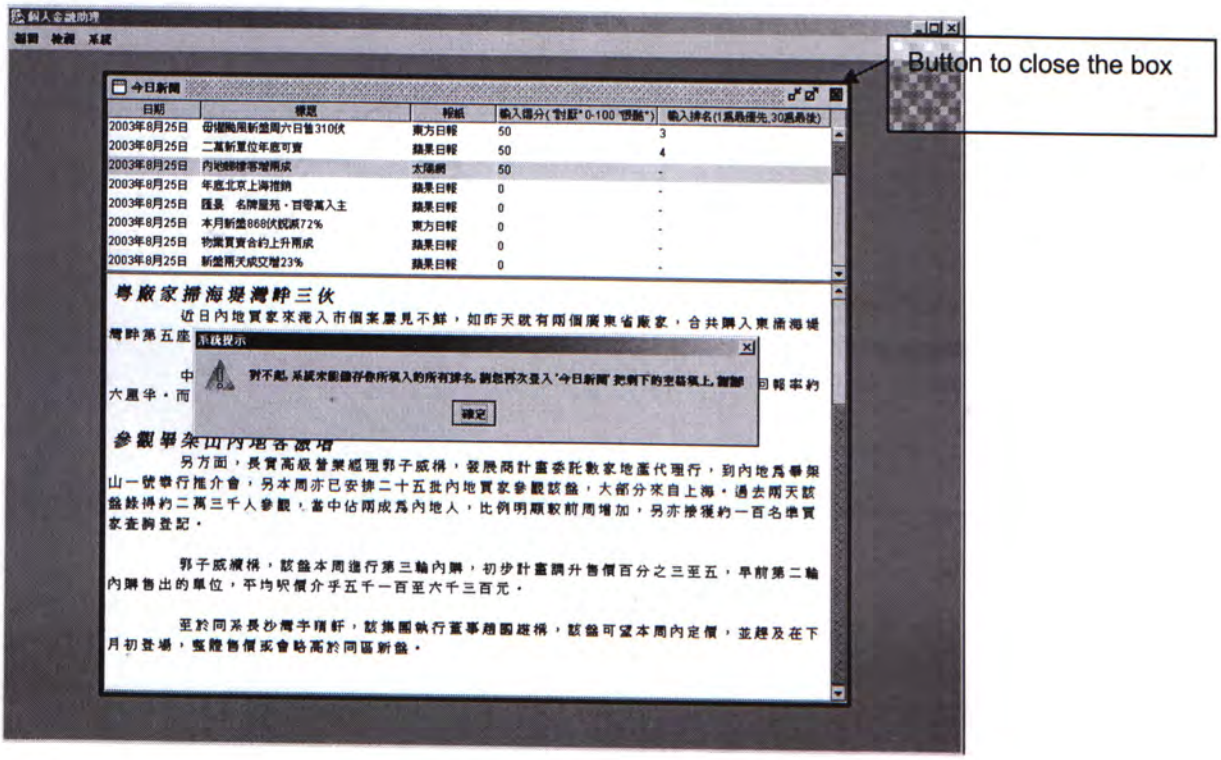
If the mark is successfully captured by the system, the highlight bar will proceed to one row down.



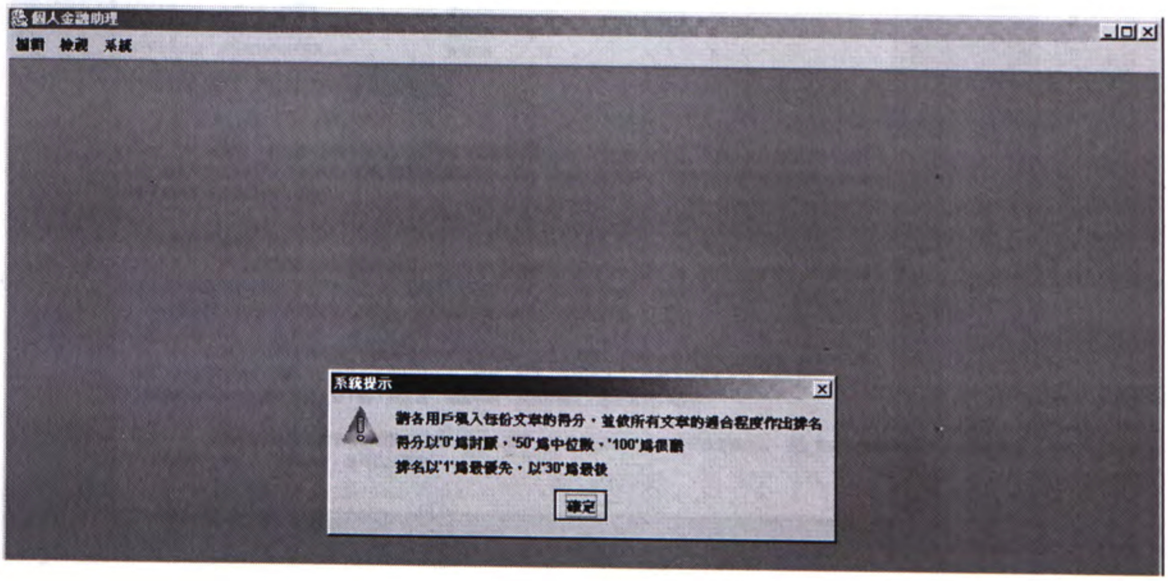
Similarily, you input the ranking in the 輸入排名 column. After you have input the ranking, again, hit "enter" key the bar will proceed to one row downwards to indicate the ranking is successfully capture.



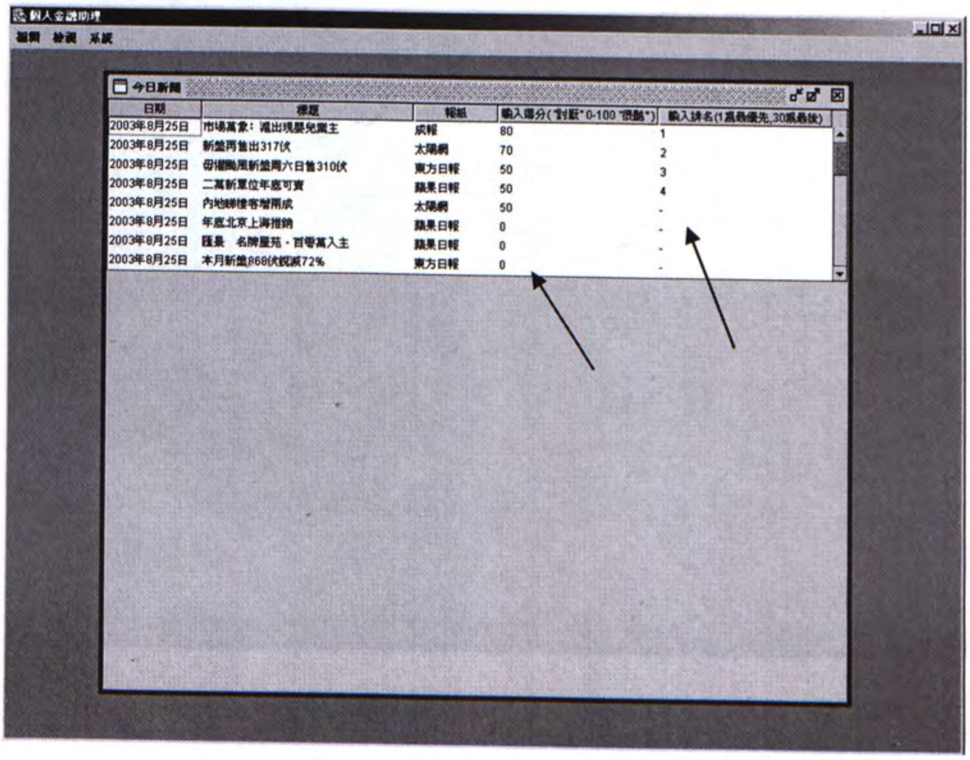
After you have input all you ratings and rankings, you can click on the "x" button to close the box. However, if you have not input all the ratings/ rankings, the following warning message will appear. You can click the 確定 button to discharge the message.

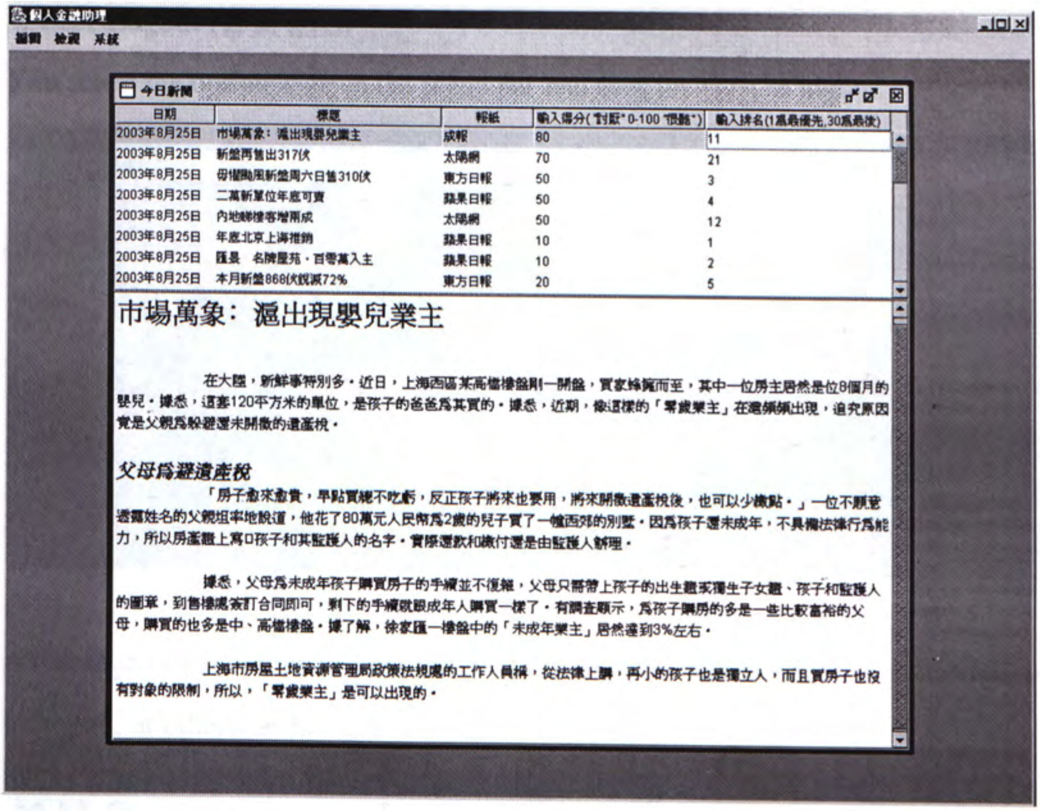


The news dialog box closed and then you have to choose the option 檢視 in the menu bar and then choose 今日新聞, to open the news articles fetched according to your profile setting, and to re-input your ratings and rankings. Again, the following dialog box appears to remind you about the rules in ratings and rakings.

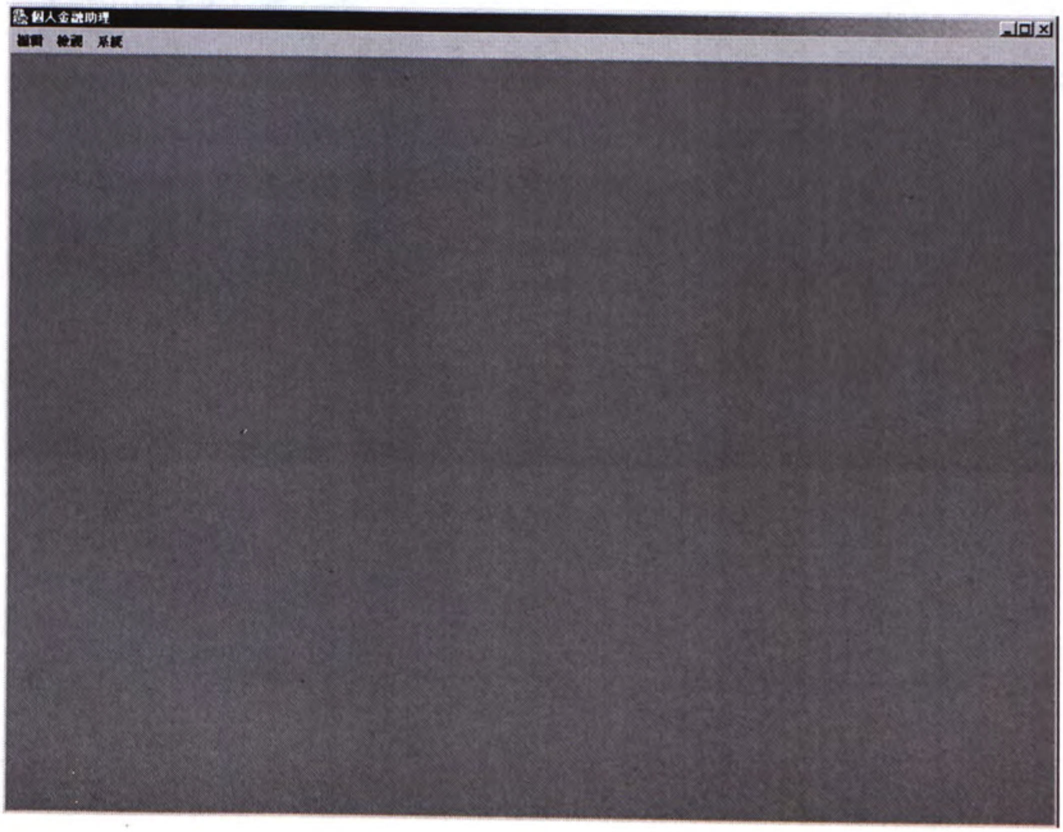


You can check which news articles you have not provided ratings or ranking yet. A "0" in the 輸入得分 indicates you have not input ratings yet while "-" in the 輸入排名 indicates you have not input ranking yet. Be sure you have input all the ratings and rankings before you close the news articles box.



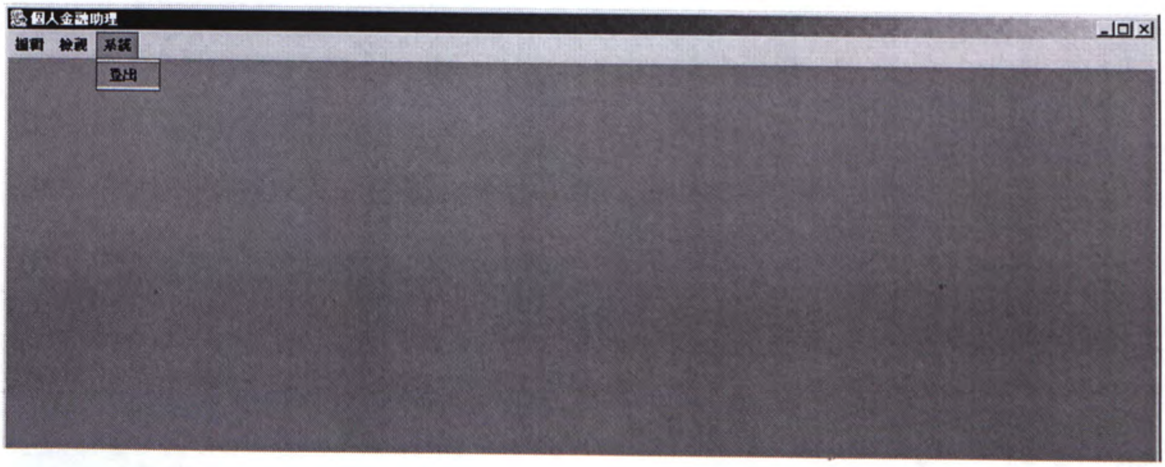


If you have input all the ratings and rankings, after you closed the news box, there will be no message box prompt out.

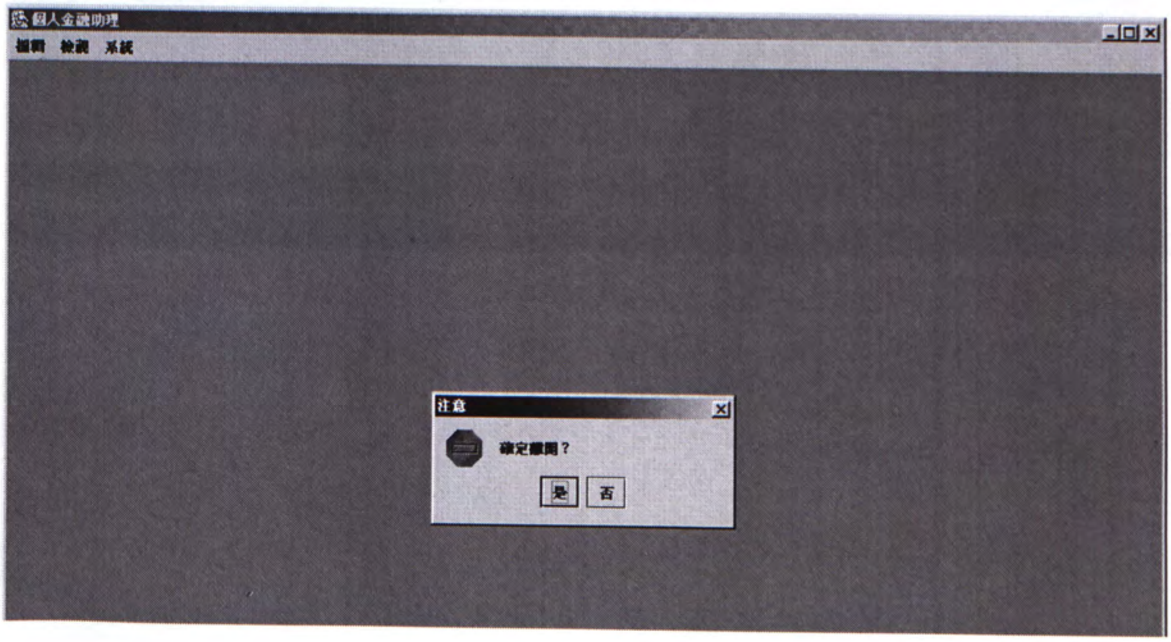


4. User Logout (會員登出)

You select the option 系統 in the menu bar and then hit 登出 to logout.



A message box will then prompt out to ask you for confirmation to logout. Hit 是 if you want to logout, or otherwise hit 否 to cancel the logout process.



After you have successfully logout, the screen will appear as follow. There is only one option 會員區域 in the menu bar.